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Cable anomaly detection driven by spatiotemporal correlation dissimilarity measurements of bridge grouped cable forces

Dong-Hui Yang [1,2], Hai-Lun Gu [2], Ting-Hua Yi [*2] and Zhan-Jun Wu [3]

[1] *State Key Laboratory of Mechanical Behavior and System Safety of Traffic Engineering Structures, Shijiazhuang Tiedao University, Shijiazhuang 050043, China*
[2] *School of Civil Engineering, Dalian University of Technology, Dalian 116023, China*
[3] *State Key Laboratory of Structural Analysis for Industrial Equipment, Dalian University of Technology, Dalian 116023, China*

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Abstract. Stayed cables are the key components for transmitting loads in cable-stayed bridges. Therefore, it is very important to evaluate the cable force condition to ensure bridge safety. An online condition assessment and anomaly localization method is proposed for cables based on the spatiotemporal correlation of grouped cable forces. First, an anomaly sensitive feature index is obtained based on the distribution characteristics of grouped cable forces. Second, an adaptive anomaly detection method based on the *k*-nearest neighbor rule is used to perform dissimilarity measurements on the extracted feature index, and such a method can effectively remove the interference of environment factors and vehicle loads on online condition assessment of the grouped cable forces. Furthermore, an online anomaly isolation and localization method for stay cables is established, and the complete decomposition contributions method is used to decompose the feature matrix of the grouped cable forces and build an anomaly isolation index. Finally, case studies were carried out to validate the proposed method using an in-service cable-stayed bridge equipped with a structural health monitoring system. The results show that the proposed approach is sensitive to the abnormal distribution of grouped cable forces and is robust to the influence of interference factors. In addition, the proposed approach can also localize the cables with abnormal cable forces online, which can be successfully applied to the field monitoring of cables for cable-stayed bridges.

Keywords: anomaly location; condition assessment; grouped cable forces; novelty detection; spatiotemporal correlation

1. Introduction

Stayed cables are the main load-bearing element of the cable-stayed bridges, and the change in the cable forces has a significant influence on the overall mechanical behavior of the bridge. After several years of service, the cable-stayed bridge is subject to long-term adverse effects (e.g., fatigue and corrosion) and environmental effects as well as various vibration effects (e.g., rain-wind induced vibration), which lead to deterioration and abnormal changes in cable forces compared with those in the normal operating condition (Li and Ou 2016, Yang *et al*. 2016). Therefore, the condition assessment of the cable-stayed forces of large-span cable-stayed bridges is important for assessing the overall mechanical behavior of bridges (Chu and Ball 2022, Nong *et al*. 2021).

At present, anomaly identification research focusing on stay cables can be divided into direct anomaly detection of stay cables (Ho *et al*. 2013) and condition evaluation of stay cables by measuring cable forces (Scarella *et al*. 2017, Tomé *et al*. 2020). The second method is the most common since cable force is the most direct monitoring index related to the condition of stay cables. Whether the cable forces are within a reasonable range will significantly affect the overall mechanical behavior and the degree of line smoothing of bridges (Zhang *et al*. 2021, Tang *et al*. 2019). Currently, for time-varying cable force identification, direct measurements, vibration-based cable force identification (Xue and Shen 2020, Hou *et al*. 2021), and noncontact cable force identification methods based on computer vision technology (Kim *et al*. 2013, Feng *et al*. 2017) can be used. However, the measured cable force in the actual operation stage is affected not only by the condition of the cable itself but also by the volume of the traffic load, environmental factors (wind, temperature, and so on) and sensor noise (Yang *et al*. 2018a, b). Namely, the multiple sources of variable factors, such as environmental actions and vehicle loads, increase the complexity of cable force condition monitoring.

To eliminate the effect of the ambient temperature, Sousa Tomé *et al*. (2019) proposed a method for early damage detection and localization of cables under the influence of environmental and operational variations and eliminated the temperature and long-term effects by combining two well-established multivariate statistical tools, MLR and PCA. Fan *et al*. (2020) proposed a strategy for early damage detection based on multivariate cointegration analysis and statistical process control, in which the effects of environmental and operational changes were damped using cointegration analysis, and the

*Corresponding author, Ph.D., Professor,
E-mail: yth@dlut.edu.cn

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cointegration residual series were used as early warning indices for cable damage warning. However, due to the redistribution effect of the internal force, the change in the cable force of a single cable may be small when the cables are damaged. In this case, the cointegration analysis method of temperature and cable force is not sensitive to identifying the cable with small damage. In contrast, Li *et al*. (2018) proposed the cable force ratio as an index reflecting the cable anomaly based on the correlation of the cable force upstream and downstream of a double cable-stayed bridge and adapted the Gaussian mixture model to fit the cable force ratio distribution to evaluate the cable condition based on the transformation of the model parameters. Peng *et al*. (2022) proposed a new method for detecting stay cables with abnormal cable forces based on matched vehicle-induced cable tension ratios, and the slope of the least-squares fitted line of the matched peak cable force between two cables on the same side for a period of time was defined as a damage sensitivity index. Although the two studies effectively avoided the interference of external environmental effects and the shortage of single-cable cointegration analysis for cable condition assessment, they both have the problems that it is difficult to guarantee the efficiency and real time of cable condition assessment and that comprehensive decision-making is required to determine the location of abnormal cables.

In recent years, with the advent of the big data era, novelty detection, pattern recognition, and machine learning have been widely used in SHM, with the aim of efficiently extracting features and pattern recognition from big data (Sun *et al*. 2020). Santos *et al*. (2017) proposed a pattern recognition and data fusion approach based on a data-driven strategy for structural health monitoring, which could detect the damage of a 1% reduction in the stiffness of a single stay cable. Pan *et al*. (2018) developed a structure diagnosis and damage detection framework based on data-driven support vector machines. A combination of a support vector machine and a time-frequency-driven nonparametric approach was used for feature extraction for the rapid condition assessment of large cable-stayed bridges. Alamdari *et al*. (2019) proposed a data analysis method based on incremental multi-directional data analysis and used incremental tensor analysis for data fusion and feature extraction, and anomaly detection of stay cable forces was performed using a class of support vector machines. Son *et al*. (2022) proposed a method to identify cable damage in cable-stayed bridges based on statistical analysis, clustering and neural network models and used a voting integration method to combine the predictions of all models to identify damaged cables in cable-stayed bridges. The method based on novelty detection has the advantages of unsupervised monitoring and the extraction of features from multisensor information, and it is expected to realize the real-time online monitoring of stay cable force. However, the current method for identifying the abnormal cable force based on novelty detection has the disadvantage that the warning index is not clear in physical meaning and is poor in explanatory ability.

To solve the problems of the existing methods in terms of the unclear physical meaning of the warning index and difficulties in anomaly localization in the assessment of cable force conditions, this paper proposes an online condition assessment and anomaly localization method of cables based on the requirements of evaluating the overall mechanical behavior of cable-stayed bridges. The rest of the paper is structured as follows: first, the basic theory of the anomaly sensitive feature vector of the vehicle-induced cable forces is introduced based on the influence surface theory; second, the online condition assessment method of grouped cable forces based on the *k*-nearest neighbor rule is proposed; third, an online anomaly isolation and localization method for stay cables is established. Furthermore, case studies using an in-service cable-stayed bridge in China are carried out. Finally, some conclusions are given in detail.

2. Anomaly sensitive feature index of grouped cable forces

2.1 Spatiotemporal correlation analysis of vehicle-induced cable forces

In the normal operation of cable-stayed bridges, the cable force is mainly generated by the static cable force, vehicle-induced cable force and environmental effect. The vehicle-induced cable force is the main factor causing the cable force to change. However, the cable force will generate random fluctuations under random traffic, so it is difficult to assess the abnormal state of the cable force by using the operational cable force as an index directly.

Therefore, the method developed in this research uses vehicle-induced cable force for analysis. However, the vehicle cases during the operation of bridges are complex and diverse. At different times, the volume, weight, and position of vehicles are also different. Li *et al*. (2018) divided the cases of random vehicles during the operations of cable-stayed bridges into five main cases, which are: single and multiple vehicles in different lanes or directions. According to the influence surface theory, the peak cable force induced by vehicles under the multivehicle case is calculated by Eq. (1)

$$T_v(p) = \sum_{j=1}^{N} \phi \eta_p\left(x_j^{\text{equiv}}, y_j^{\text{equiv}}\right) W_j^{\text{equiv}} \tag{1}$$

where $T_v(p)$ represents the change in the cable force of the cable p induced by the vehicle; x_j^{equiv} and y_j^{equiv} represent the equivalent transverse position and longitudinal position of the j vehicle (the multiaxle action) on the bridge, respectively; W_j^{equiv} is the equivalent concentrated load under the action of each axle load of the j vehicle; $\eta_p(\cdot)$ is the internal force influence coefficient of the cable p; ϕ is the dynamic amplification coefficient under the action of vehicle-bridge interaction; and N is the total number of vehicles on the bridge at a certain time. Note that this study focuses on large-span cable-stayed bridges, so the wheelbase and axle load distributions are ignored in the theoretical deduction of this section and simplified to equivalent concentrated forces for the common vehicle cases (i.e., with a smaller wheelbase). For the rare multiaxle trailers, such cases are excluded in the single vehicle identification criterion in section 4.3.

In the operation of a bridge, the spatial distribution of vehicles on the bridge is very complex, and the cable forces induced by multiple vehicles are complicated to consider. Furthermore, the abnormal condition of the cable under the interaction of multiple working conditions may be masked. Therefore, the case of a single vehicle is mainly analyzed and the temporal and spatial correlation of the vehicle-induced cable forces are discussed. It is assumed that there is only a single vehicle driving in a specific lane of the bridge in a certain time period, and then the vehicle-induced cable force can be calculated using Eqs. (2) and (3).

$$T_v(p) = W^{\text{equiv}}\eta_p(x, y_p, \theta_p) \tag{2}$$

$$T_v(q) = W^{\text{equiv}}\eta_q(x, y_q, \theta_q) \tag{3}$$

where $T_v(p)$ and $T_v(q)$ represent the changes in the cable force of cable p and cable q on the same side (upstream or downstream) induced by the vehicle; W^{equiv} is the equivalent load under the action of each axle load of the single vehicle; $\eta_p(x, y_p, \theta_p)$ and $\eta_q(x, y_q, \theta_q)$ are the internal force influence surface of cable p and cable q, θ_p and θ_q are the inclination angles of cable p and cable q, respectively. The internal force influence surface is a dimensionless parameter related only to the structural property of the cable, the position of the vehicle load (i.e., the lateral and longitudinal position of the vehicle load) and the inclination angle of the cable. It should be noted that the bridge-vehicle interaction effect can be ignored for large span cable-stayed bridges (Guo and Xu 2001), and therefore, Eqs. (2) and (3) are not considered for the factor's influence on the vehicle-induced cable forces. Fig. 1 gives an illustration of a two-axle truck driving in a certain lane of the bridge. When the vehicle drives to the cross section where the cable is located, the vehicle-induced cable force reaches the maximum (i.e., the peak force of the cable).

According to the linear elasticity assumption, the internal force influence surface of the cable can be simplified by the product of transverse and longitudinal distribution coefficients of cable

$$\eta(x, y, \theta) = \eta(x, \theta) \cdot \eta(y) \tag{4}$$

where $\eta(x, \theta)$ and $\eta(y)$ are the transverse and longitudinal distribution coefficients of a cable, respectively. Therefore, in the single vehicle case, the following correlation can be deduced from the cable force distribution characteristics on the same side.

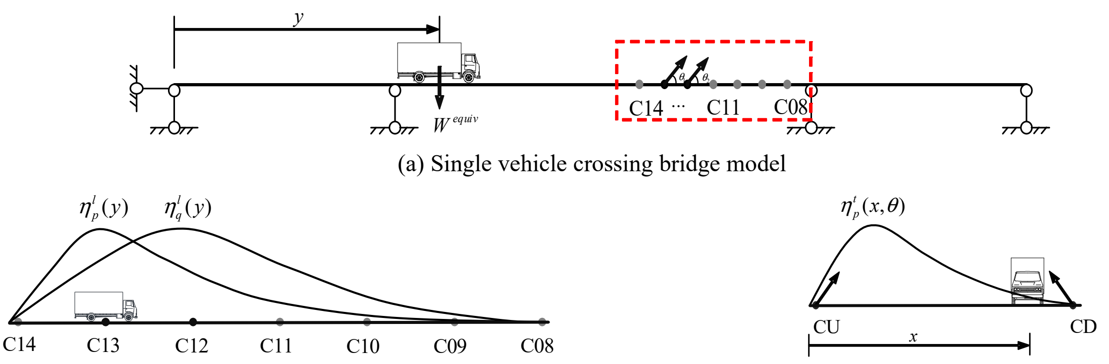
$$\begin{aligned} T_v(p) &= \frac{\eta_p(x, \theta_p) \cdot \eta_p(y_p)}{\eta_q(x, \theta_q) \cdot \eta_q(y_q)} \times T_v(q) \\ &= \zeta\{\theta_i, y_i | (i = p, q)\} T_v(q) + e \end{aligned} \tag{5}$$

In the actual operation stage, the random traffic conditions and external environmental factors of the bridge are complex and variable, and the single-vehicle case in theory is rare and difficult to separate. Therefore, e in Eq. (5) is the calculation error caused by the vehicles in other lanes, vehicle-bridge interaction and environmental interference. During a vehicle driving over the first and second cables on the same side (without considering the effect of vehicle lane change), the ratio of the transverse distribution coefficient of the two cables is only related to the inclination angles θ_p and θ_q. Therefore, it can be concluded from Eq. (5) that there is a stable correlation between the cable forces on the same side cables under the single-vehicle case, and it can be considered as a constant value related only to the longitudinal position of the cable, inclination angle and longitudinal distribution influence coefficient of the corresponding cable.

2.2 Anomaly sensitive feature vector establishment

The cable-stayed bridge is a structure of a composite force system, where all the cables are anchored to the common main girder and main tower. Therefore, it shows a high integrity performance in the force. When the structure is significantly changed, it will definitely lead to a significant change in the characteristics of the cable force distribution. However, due to the internal force redistribution effect of the cables, there may still be one or some of the cables in the normal range. Therefore, it is considered a more reasonable and reliable method to evaluate the condition of the cables based on the change in the force distribution characteristics of the grouped cables.

It can be concluded from the previous section that the peak cable force induced by the single-vehicle case on the



(a) Single vehicle crossing bridge model

(b) Single vehicle crossing from C14 to C08

(c) Cross section diagram

Fig. 1 Illustration of a single vehicle on the bridge same side can indicate the spatial correlation and the inherent properties of the structure. Eq. (6) is an anomaly sensitive feature vector based on the distribution characteristics of the grouped cable forces. It indicates the feature vector consisting of the change in the vehicle-induced force of each cable when the same vehicle passes through each cable on the same side in turn. Therefore, the condition of the cable can be evaluated based on the change in the distribution characteristics of the grouped cable forces.

$$\boldsymbol{x} = [x_1\ x_2\ \cdots\ x_i\ \cdots x_n]^T \tag{6}$$

where $\boldsymbol{x}$ is the anomaly sensitive feature vector of the grouped cables and x_i is the change in the vehicle-induced cable force of the first cable under the single vehicle case. Furthermore, as shown in Eq. (7) the feature matrices are comprised of the abnormal sensitivity feature vectors of the grouped cables for different single-vehicle cases in a time series. Therefore, the feature matrices can not only reflect the characteristics of the spatial distribution of the grouped cable forces but also have time series information of the grouped cable forces.

$$\boldsymbol{X} = [\boldsymbol{x}_1\ \boldsymbol{x}_2\ \boldsymbol{x}_3 \cdots \boldsymbol{x}_i \cdots \boldsymbol{x}_m] = \begin{bmatrix} x_{11} & x_{21} & \cdots & x_{m1} \\ x_{12} & x_{22} & \cdots & x_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1n} & x_{2n} & \cdots & x_{mn} \end{bmatrix} \tag{7}$$

where $\boldsymbol{X}$ is the abnormal sensitivity matrix of the grouped cable forces and $\boldsymbol{x}_m$ is the anomaly sensitivity vector of the cable force consisting of the change in cable force on the same side induced by the m-*th* single vehicle case. x_{mn} is the change in the cable force of the n cable induced by the m-*th* single vehicle.

3. Anomaly detection method for cable forces

To ensure the real-time accuracy of cable force condition assessment and anomaly location, the adaptive anomaly detection method based on the *k*-nearest neighbor (*k*-NN) rule is introduced as a global unsupervised anomaly monitoring technology (Verdier and Ferreira 2010). The anomaly detection method for cable forces that mainly focuses on the objectives of anomaly detection and location is then established. Then, the implementation procedure is explained in detail.

3.1 Dissimilarity measurements of anomaly sensitive index

According to Eq. (7), to accurately evaluate the grouped cable forces condition, it is necessary to measure the dissimilarity of the proposed grouped cable forces index. In other words, the differences between two abnormal-sensitive feature vectors of cable force should be transformed into scalars for comparison. However, under the actual operation conditions of the bridge, the number of theoretical single vehicle cases is very small. In Eq. (5), the cable force induced by a single vehicle ignores the influence of the vehicles in other lanes, vehicle-bridge interaction effects and the influence of the external environment. In which, the major error is the cable force induced by vehicles on other lanes. Therefore, when the change of the group cable forces distribution characteristics is small due to the structural changes of the long-span cable-stayed bridges, that is to say, when the damaged level of a long-span cable-stayed bridge is not significant, it is possible that the slight abnormal deviation of the cable forces may be masked under the comprehensive influence of the above factors.

Therefore, a global unsupervised anomaly detection algorithm is introduced, namely, an adaptive anomaly detection method based on the *k*-nearest neighbor rule. The central idea behind the method is that similar vehicle cases generate similar grouped cable force distribution characteristics. Therefore, similar observations have close neighbors in the training data, while dissimilar observations are located far from their closest neighbors (Sarmadi and Karamodin 2020). In other words, the distance of an anomaly feature vector of grouped cable forces to the nearest neighboring training samples is much greater than the distance of a normal feature vector of grouped cable forces to the nearest neighboring training samples.

According to the spatiotemporal correlation theory of vehicle-induced cable forces, the influence of vehicles in other lanes, vehicle-bridge interaction effects and other factors are regarded as external environmental interference. Therefore, the interference of external factors on the anomaly detection results can be effectively avoided by using an adaptive anomaly detection method based on the k-nearest neighbor rules, that is, it is highly robust to environmental interference. In addition, the anomaly detection algorithm can realize the online condition monitoring of the grouped cable forces.

For the online condition monitoring of the grouped cable forces, the adaptive anomaly detection method based on the *k*-nearest neighbor rule consists of two main parts, including offline training and online condition monitoring, in the inspection phase. Additionally, the method is adaptive in the sense that, for each observation under monitoring, the Mahalanobis distance is used with a different covariance matrix, obtained on the nearest neighbors of each observation.

3.1.1 Offline training

The feature vector of grouped cable forces acquired under normal conditions is used as the training dataset. The procedure is as follows:

Step 1: Calculate the Euclidean distance of the i -*th* anomaly sensitive feature vector of cable force $\boldsymbol{x}_i$ from the other feature vectors in the training set. One can obtain the order statistic $\boldsymbol{x}_{(1)}, \ldots, \mathbf{x}_{(n)}$. Then, the first K nearest neighbors of $\boldsymbol{x}_i$ are extracted and defined as $\bar{\boldsymbol{x}}_1, \ldots, \bar{\mathbf{x}}_K$.

Step 2: Subsequently, utilize the first K nearest neighbors $\bar{\boldsymbol{x}}_1, \ldots, \bar{\mathbf{x}}_K$ of $\boldsymbol{x}_i$ to estimate the local covariance matrix using Eq. (8)

$$\boldsymbol{S}_K(\boldsymbol{x}_i) = \frac{1}{K-1}\sum_{j=1}^{K}(\bar{\boldsymbol{x}}_j - \bar{\boldsymbol{m}})(\bar{\boldsymbol{x}}_j - \bar{\boldsymbol{m}})^T \tag{8}$$

where $\bar{\boldsymbol{m}}$ is the empirical mean vector of the K neighbors;

Step 3: Once again, find the new k nearest neighbors relative to the Mahalanobis squared distance (MSD) used with $\bar{\boldsymbol{m}}$ and $\boldsymbol{S}_K(\boldsymbol{x}_i)$ of $\boldsymbol{x}_i$ in the training set and define them as $\breve{\boldsymbol{x}}_1, \ldots, \breve{\boldsymbol{x}}_k$. Note that the selection principles of K and k have been described (Verdier and Ferreira 2010).

$$d_M = (\boldsymbol{x}_i - \bar{\boldsymbol{m}})^T \boldsymbol{S}_K^{-1}(\boldsymbol{x}_i)(\boldsymbol{x}_i - \bar{\boldsymbol{m}}) \tag{9}$$

Step 4: Calculate the cumulative distance of the first k nearest neighbors using Eq. (10) and define it as the dissimilarity measurement index (DMI) of the grouped cable force distribution features at different times.

$$\mathrm{DMI}_{i,\mathrm{lim}} = \sum_{j=1}^{k} \left(\mathbf{x}_i - \breve{\mathbf{x}}_j\right)^{\boldsymbol{T}} \boldsymbol{S}_K^{-1}(\mathbf{x}_i)\left(\mathbf{x}_i - \breve{\mathbf{x}}_j\right) \tag{10}$$

Step 5: The determination of a threshold limit τ_α is then achieved using kernel density estimation (KDE) using the ststistics $\Theta_{\mathrm{lim}} = \left[\mathrm{DMI}_{1,\mathrm{lim}}, \mathrm{DMI}_{2,\mathrm{lim}}, \ldots, \mathrm{DMI}_{n,\mathrm{lim}}\right]^T$ in the training dataset (Jiang and Yan 2014). In addition, α is always set to 0.01 according to the 99% confidence limit criterion. In the long-term monitoring of bridges, the threshold value can be updated at a certain time interval to ensure that the threshold value is reasonable for the bridge in normal aging condition (Fan *et al*. 2020, Yang *et al*. 2022).

3.1.2 Online monitoring

Step 1: Find the first K nearest neighbors of the i *-th* anomaly sensitive feature vector of cable force $\boldsymbol{z}_i$ in the training set via the ESD and define $\bar{\boldsymbol{z}}_1, \ldots, \bar{\boldsymbol{z}}_K$.

Step 2: estimate the local covariance matrix $\boldsymbol{S}_K(\boldsymbol{z}_i)$ using the first K nearest neighbors $\bar{\boldsymbol{z}}_1, \ldots, \bar{\boldsymbol{z}}_K$ of $\boldsymbol{z}_i$ as in Eq. (8).

Step 3: Once again, find the new k nearest neighbors, relative to the MSD with $\bar{\boldsymbol{m}}$ and $\boldsymbol{S}_K(\boldsymbol{z}_i)$, of $\boldsymbol{z}_i$ in the training set. Calculate the cumulative distance as the dissimilarity measurements index (DMI) of the grouped cable forces distribution features.

Step 4: Apply the online condition monitoring rule: if DMI exceeds the threshold τ_α, then the anomaly sensitive feature vector of the cable force $\boldsymbol{z}_i$ is out of control and indicates that the grouped cable force distribution features have changed. Subsequently, repeat the previous three steps for the next feature vector $\boldsymbol{z}_{i+1}$.

3.2 Abnormal cable isolation

When the dissimilarity measurement index (DMI) in Eq. (10) exceeds the threshold, it indicates that the distribution characteristics of the grouped cable forces have changed greatly. Therefore, an effective method is needed to accurately identify the cable with abnormal cable forces. In this section, the complete decomposition contributions (CDC) method (Alcala and Qin 2011, Huang *et al*. 2016) is used to decompose the feature matrix of the grouped cable forces and build an anomaly isolation index for identifying the cable with abnormal cable forces. Eq. (10) can be further expressed as

$$\begin{aligned}\mathrm{DMI} &= \sum_{i=1}^{k} \boldsymbol{X}_i^T \mathbf{S} \boldsymbol{X}_i = \sum_{i=1}^{k} \left\| \mathbf{S}^{\left(\frac{1}{2}\right)} \boldsymbol{X}_i \right\|^2 \\ &= \sum_{i=1}^{k} \left[\sum_{j=1}^{n} \left(\xi_j^T \mathbf{P} \boldsymbol{\Lambda}^{-(1/2)} \mathbf{P}^T \boldsymbol{X}_i \right)^2 \right] = \sum_{j=1}^{n} CDC_j\end{aligned} \tag{11}$$

where

$$\boldsymbol{X}_i = \boldsymbol{x}_i - \breve{\boldsymbol{x}}_j \tag{12}$$

$$\boldsymbol{S} = \boldsymbol{S}_K^{-1}(\boldsymbol{x}_i) \tag{13}$$

$$\boldsymbol{S} = \boldsymbol{P}\boldsymbol{\Lambda}^{-1}\boldsymbol{P}^T \tag{14}$$

where, $\boldsymbol{\Lambda} = diag(\lambda_1, \lambda_2, \ldots, \lambda_n)$ represents the diagonal matrix consisting of all n eigenvalues, λ_i represents the i eigenvalue, $\boldsymbol{P} = [\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_n]$ represents the standard orthogonal matrix consisting of all the n eigenvectors, $\boldsymbol{p}_i$ represents the *i-th* eigenvector;

DMIis the summation of n variable contributions, and n is the number of the investigated cable. When it exceeds the threshold, it can be considered that the grouped cable forces are in an abnormal condition.

$$CDC(j) = \sum_{i=1}^{k} \left(\xi_j^T \boldsymbol{P}\boldsymbol{\Lambda}^{-(1/2)} \boldsymbol{P}^T \boldsymbol{X}_i \right)^2 \tag{15}$$

Here, CDC represents the isolation index of abnormal cable forces. When the index corresponding to a certain variable increases significantly, the cable with abnormal cable forces can be identified. ξ_j represents the j *-th* column of the identity matrix. That is, the *j-th* element is 1, and the remaining elements are 0.

$$\xi_j = [0 \quad 0 \cdots 1 \cdots 0]^T \tag{16}$$

4. Case study

The SHM data acquired from a long-span cable-stayed bridge in service in China are used to verify the effectiveness of the proposed approach.

4.1 Overview of bridge SHM data

This study utilizes the cable force monitoring data of a cable-stayed bridge in China to verify the proposed method (Bao *et al*. 2021). Fig. 2 shows an illustration of the bridge, which is a cable-stayed bridge in the form of double-tower and double-cable-plane and accommodates six traffic lanes. This cable-stayed bridge consists of 84 pairs of cables (168 cables) symmetrically distributed in the double cable planes, that is, 84 cables on the upstream side and 84 cables on the downstream side. The cable tension dataset was collected from the 14 cables, which are the cables of CU08-CU14 and CD08-CD14 on the main span on the south tower

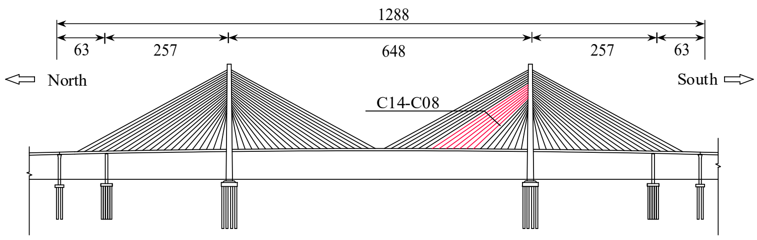
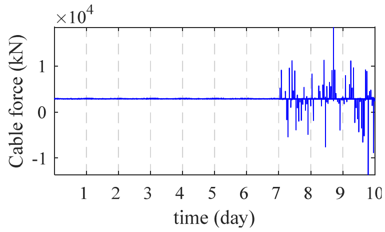
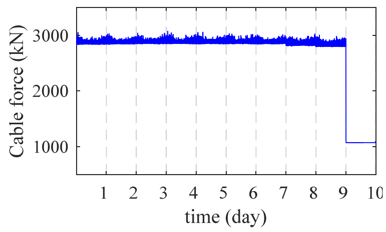


Fig. 2 The investigated cable-stayed bridge (units: m).



(a) CU13 in ten selected days



(b) CD13 in ten selected days

Fig. 3 Raw cable forces of cable pair C13 on ten selected days

side, where “U/D” stands for cables on the upstream side and downstream side, respectively. The dataset includes ten-day cable force monitoring data from 2006-05-13 to 2006-05-19, 2007-12-14, 2009-05-05, and 2011-11-01. The sampling frequency is 2 Hz. It is known that in 2011, one out of the 14 cables was damaged (the damage is rupture of wires), and the cable on the other nine days was in the normal state.

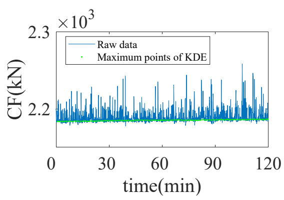
4.2 Extraction of vehicle-induced cable forces

The raw cable force data contain outliers due to the influence of the sensor fault. Fig. 3 shows the raw cable forces of cable pair C13 on ten selected days, from which it can be observed that the cable force of the cable CU13 has obvious abnormal fluctuations from the seventh day to the tenth day. Besides, the cable force of the cable CD13 dropped sharply on the tenth day. Therefore, the distribution test method (Peng *et al*. 2022) was adopted to further judge and eliminate the abnormal outliers of the raw cable force data.

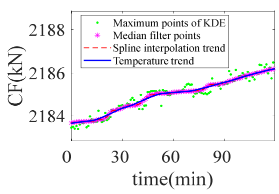
The monitored cable forces at the operation stage of the cable-stayed bridge are often the result of multiple effects, which mainly include noise, temperature effects, and effects induced by live loads and dead load. The effect of vehicle-induced cable force has the characteristics of short-term mutation, which causes the cable force to generate spikes with small amplitudes. Temperature-induced cable force is the main environmental factor, and the change period is long, while other random interferences have a relatively high frequency.

Therefore, according to the different characteristics of the cable force change induced by different effects, the time-varying cable force can be decomposed into two parts, which are the cable force trend caused by environmental factors such as the dead load and temperature effect and the local peak of the cable force due to the random vehicle load effect.

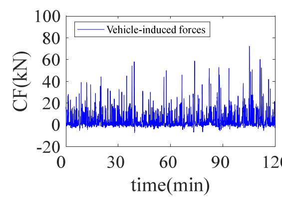
A method is proposed for online extraction of the vehicle-induced cable forces based on the moving-window analysis. The core idea is to determine the temperature-induced cable forces by a statistical method (Ren *et al.* 2019) and to update them online by moving-window analysis. First, the real-time cable forces for a certain time interval are extracted and the kernel density estimation (KDE) is used to fit the measured cable force data, and the cable force corresponding to the maximum value of probability density is considered as the static cable force that is not effected by vehicle loads. Subsequently, a moving-window analysis method (the window length is set to 15 minutes) is used to update the static cable forces at a certain time step length that is set to be 1 minute. The variation of the extracted static cable forces can be considered to be affected only by variable temperature.



(a) Raw data and maximum points of KDE



(b) Temperature effect



(c) Vehicle-induced forces

Fig. 4 Procedures for extracting the vehicle-induced cable forces.

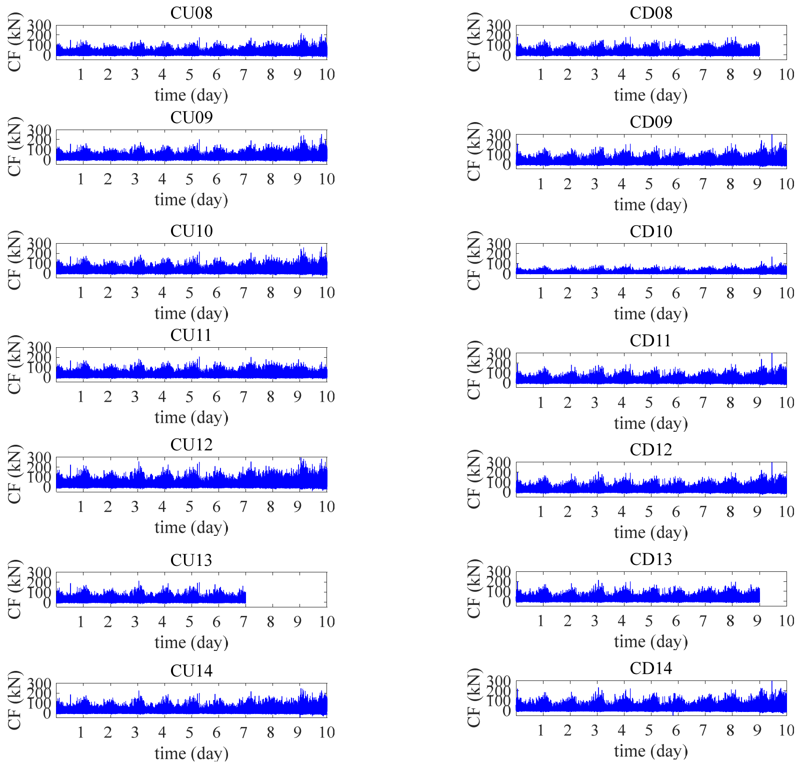


Fig. 5 The vehicle induced cable forces of cable pair C08 to C14 in ten selected days

Second, the extracted static cable forces are furtherly processed by median filtering, spline interpolation and the moving average method (MAM) to smooth the temperature-induced cable forces. Finally, by subtracting the static cable forces from the raw cable forces, the vehicle-induced cable forces can be obtained. Fig. 4 shows the extraction procedures of the vehicle-induced cable force in detail and Fig. 5 shows the vehicle-induced cable forces after removing the temperature trend and the outliers.

4.3 Anomaly sensitive feature extraction of grouped cables

The real-time cable force is composed of relatively stable larger values caused by the dead load or environmental effect and peaks with small amplitude caused by vehicles. Due to the influence of random vehicles, the vehicle-induced cable force peaks may be induced by single-vehicle cases or multivehicle complex cases. The single-vehicle case can be simplified as a concentrated force, which is the focus of this study.

For the cable whose influence line is in the form of a single peak, the greatest influence on the cable force is only when a single vehicle is driving in a specific area near the cable, which is consistent with the method based on geometric characteristics of the peak to identify the vehicle location and vehicle distribution characteristics (such as single vehicle or multiple vehicles).

Therefore, this study identifies and extracts a single vehicle case based on the geometric characteristics of the peak number. In more detail, the extraction process of the single-peak condition mainly finds that the valley values on both sides of the corresponding peak are less than a certain threshold (2 kN is taken to reduce the influence of cable

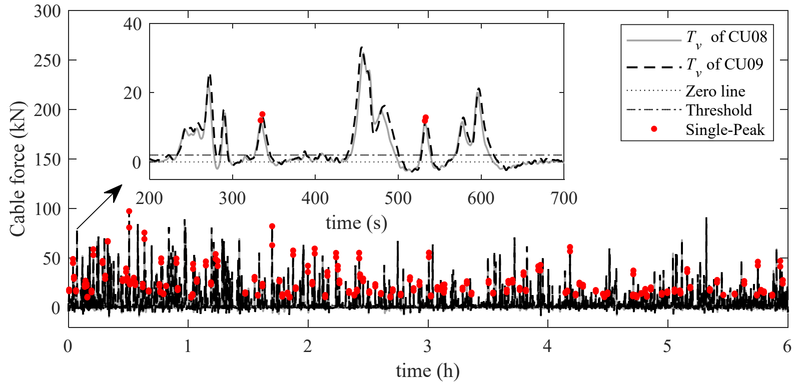
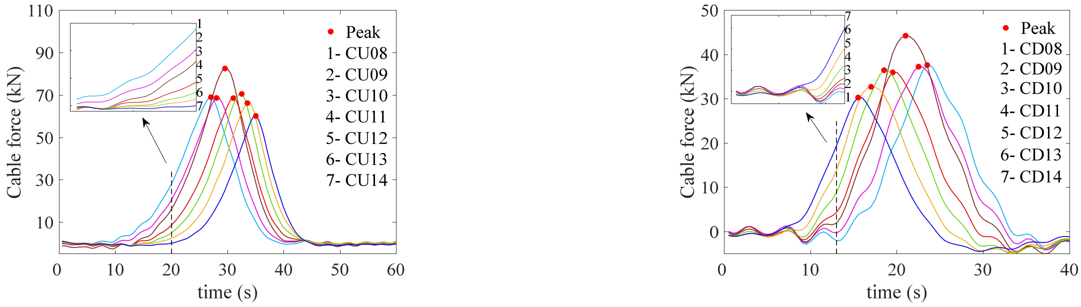


Fig. 6 Vehicle-induced cable tension of CU08 and CU09



(a) Upstream side (b) Downstream side

Fig. 7 The cable tension change induced by a vehicle

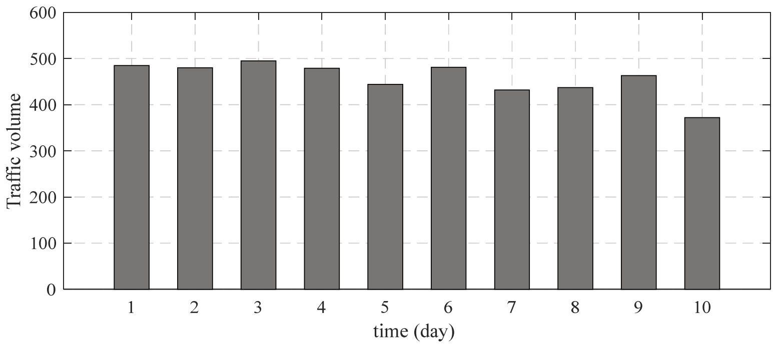


Fig. 8 The traffic volume of single vehicle in ten selected days

force fluctuations induced by the free vibration of vehicles crossing the bridge). Moreover, the width of the peak (that is, the time when a single vehicle acts on the corresponding cable) cannot be too short to exclude the influence of external abnormal fluctuations, and the time used in this study is 10 s. In addition, we eliminate the influence of noise and vehicle-bridge interactions as much as possible.

Therefore, the focus of this study is the peak value larger than 10 kN. The single-peak extraction results of CU08 and CU09 for a certain time period are shown in Fig. 6.

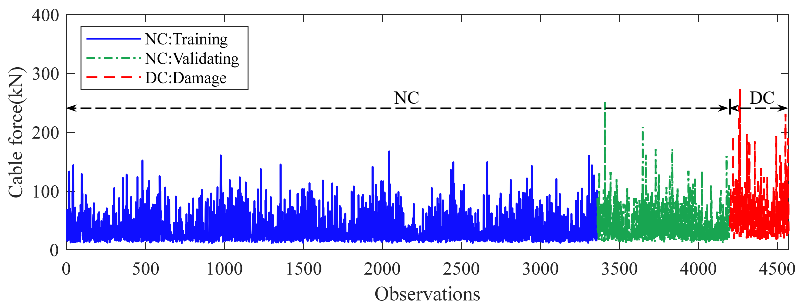
The cable force peak matching procedure finds the peak value between different cables on the same side that are induced by the same vehicle, and it is the premise of constructing the abnormal-sensitive feature vectors of the cable force. The procedure is mainly divided into two steps: first, the single-peak identification method based on the geometric characteristics of a single-peak number is used to identify and locate the single-vehicle case; second, the next peak in the driving direction is searched to achieve matching peak values induced by the same vehicle. Also, from section 2.1, it can be obtained that there is a time delay in reaching the peak cable force when a single vehicle in theory passes through different cables at the same side. Figs. 7(a)-(b) show this in detail. It should be noted that the search time range cannot be too large or too small. If the time range is too large, multiple peaks may overlap. On the other hand, it may cause the target peak to be missed.

The peak matching procedure is performed for the five cables on the upstream side (i.e., CD08, CD09, CD10, CD11, and CD12). Finally, there are 4568 single vehicle cases that meet the above criteria for ten days, with an average of more than 400 vehicles per day. Fig. 8 shows the traffic volume of a single vehicle on ten selected days in detail. Moreover, it can be seen that the number of single-vehicle cases in the first nine days is approximately 500 vehicles per day, and the daily fluctuations are very small. However, on the tenth day, the traffic volume of a single vehicle decreased greatly compared with the previous one. Therefore, it is estimated that the traffic flow was restricted to ensure the normal operation of the bridge when the cable was damaged. Meanwhile, it also proves that the proposed single-vehicle identification method and peak matching criterion can identify the single-vehicle condition well, thus ensuring the validity of the extracted abnormal-sensitive feature vectors of cable force.

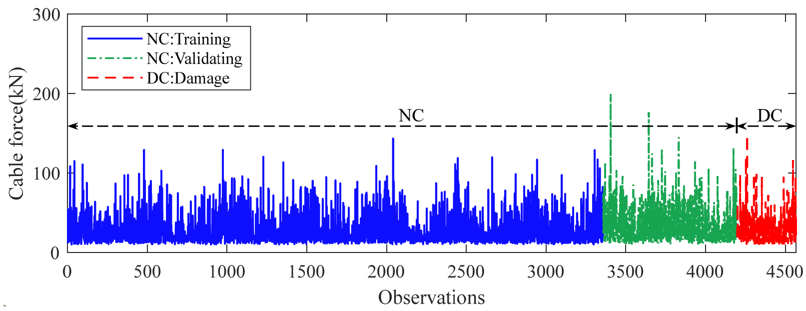
4.4 Anomaly detection and location results

To validate the effectiveness and capability of the new proposed condition assessment and anomaly location of cable forces, case studies were conducted using the sensitive feature vectors of cable forces extracted in Section 4.3. One out of the 14 cables was damaged (the damage was rupture of wires) in 2011, and the cables on the other nine days were in the normal state. Therefore, the feature vectors extracted from the first nine days were used as the training set, and the feature vectors extracted from 2011 (i.e., the last day) were used as the testing set to verify the proposed method.

For offline learning during the training period, the training dataset (matrix) was composed of 80% of the feature vector of grouped cable forces of the normal condition, that is, the measurements 1- 3357th of the feature vector of grouped cable forces of the five cables on the



(a) Cable CU11



(b) Cable CU12

Fig. 9 Peak value of the vehicle-induced cable forces

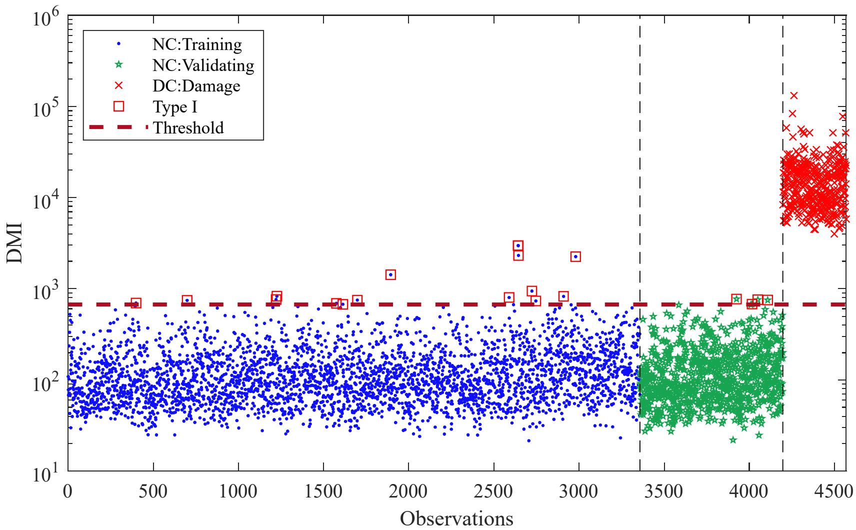


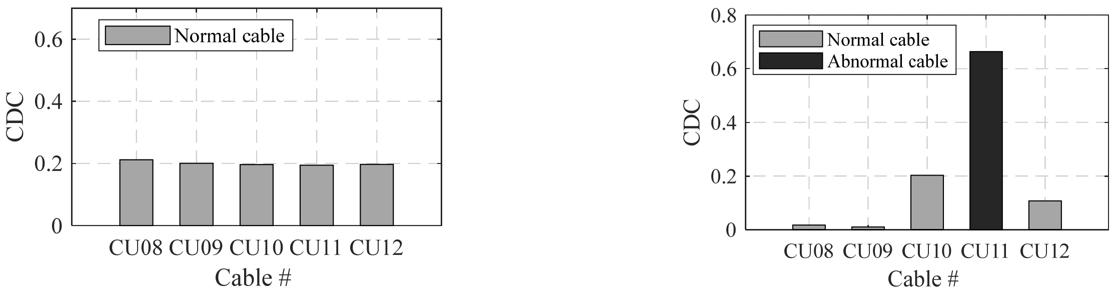
Fig. 10 Results of early anomaly detection

same side produced the training matrix $\boldsymbol{X} \in \boldsymbol{R}^{5\times3357}$, and the training matrix involved 3357 feature vectors $\boldsymbol{x}_1\ \boldsymbol{x}_2\ ...\ \boldsymbol{x}_{3357}$ of 5 variables.

On the other hand, it should be noted that the remaining 20% of the feature vectors of the normal condition (i.e., $\boldsymbol{x}_{3358}\ ...\ \boldsymbol{x}_{4196}$) constitute the validation set to verify the correctness and applicability of the proposed method. Finally, the 372 abnormal-sensitive feature vectors of cable force on the last day were extracted as the testing set (i.e., $\boldsymbol{z}_1\ ...\ \boldsymbol{z}_{372}$). Fig. 9 shows the vehicle-induced peak of the cable force of CU11 and CU12. Obviously, there is no obvious abnormal fluctuation on the tenth day only from the peak value of the vehicle-induced cable forces. Therefore, it is difficult to detect a cable with an abnormal cable force.

The proposed method is used for online monitoring of the condition of the grouped cable forces. Fig. 10 shows that all of the dissimilarity measurement indices of the grouped cable forces exceed the threshold on the tenth day, indicating that one or more cable forces are abnormal on the tenth day. This also confirms the previous conclusion that one out of the 14 cables was damaged in 2011.

According to the abnormal isolation method proposed in Section 3.2, the abnormal localization of the cable with abnormal cable forces is carried out. The results of abnormal isolation are shown in Fig. 11. In the training phase, that is, the normal condition, each variable in the feature vector contributes to the dissimilarity measurements index (DMI) to a similar extent, and each variable is



(a) Contribution analysis of training phase (b) Contribution analysis of testing phase

Fig. 11 Anomaly isolation result using CDC

approximately 20%. In the testing stage, it can be seen that the contribution of each variable to the dissimilarity measurement index changes significantly, and the fourth variable (i.e., CU11) contributes more than 60%, which is significantly larger than those of the other variables.

Notably, the contributions of the third and fifth variables, representing CU10 and CU12, respectively, are also larger than those of the first and second variables, which is related to the integrity of the force between the cables. Nonetheless, the fourth variable, which represents CU11, contributes the most to the dissimilarity measurement index, so the most likely damaged cable can be determined as CU11.

5. Conclusions

As the stay cables are the key components in cable-stayed bridges, the evaluation of cable force condition is important to ensure structural safety. An online condition assessment and anomaly localization method is proposed for stay cables based on the spatiotemporal correlation of grouped cable forces, and the following conclusions are drawn:

- Based on the structural influence surface theory, a cable anomaly sensitive feature index is established based on the force distribution characteristics of grouped cables. This index can reflect not only the intrinsic property changes of the cables, but also the time variation and spatial positions information of the grouped cables. This index can effectively reflect the overall mechanical behaviors of stay cables.
- An adaptive anomaly detection method based on the *k*-nearest neighbor rule is adopted, and the anomaly sensitive feature vector under the abnormal condition is used as the testing set for the online condition evaluation of the grouped cable forces. This method can effectively eliminate the interference of environmental factors and vehicle loads under the single-vehicle case, and the online condition assessment of grouped cable forces can be achieved.
- An online anomaly isolation and localization method for stay cables is established. When the dissimilarity measurements index exceeds the threshold, the complete decomposition contributions method is used to decompose the feature matrix of the grouped cable forces and an anomaly isolation index is obtained for identifying the cable with abnormal cable forces.
- Case studies were carried out for a cable-stayed bridge equipped with a structural health monitoring system, and it can be verified that the proposed method can be feasibly applied to abnormal cables detection and location based on the real monitoring data. The condition assessment and anomaly localization results also demonstrate that the cable with abnormal cable forces can be successfully identified through the proposed method.

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