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| **Vortex-induced Vibration Identification of Bridge Cables Applying Multiple Indicators and Clustering Algorithm** |
| **Jinghang Weng 1, Lin Chen 2, Limin Sun 3, \*, Xiaolong Li 4, Zhaoyue Wang 5**  1 Master Candidate; Department of Bridge Engineering, College of Civil Engineering, Tongji University; Shanghai 200092, China; 2132499@tongji.edu.cn  2 Associate Professor; Department of Bridge Engineering, College of Civil Engineering, Tongji University; Shanghai 200092, China; linchen@tongji.edu.cn  3 Professor; State Key Laboratory of Disaster Reduction in Civil Engineering; Department of Bridge Engineering, College of Civil Engineering, Tongji University; Shanghai Qizhi Institute; Shanghai 200092, China; lmsun@tongji.edu.cn  \*Corresponding Author  4 Master; China Communications Construction Group Corporation Limited; Beijing 100101, China; lixiaolong@hpdi.com.cn  5 Master; China Communications Construction Group Corporation Limited; Beijing 100101, China; wangzhaoyue136966@163.com |

**ABSTRACT**

Vortex-induced vibration, among all the anomalous oscillations, is one of the most common jeopardies facing cable-stayed bridge cables and suspension bridge cables. Typically, this kind of vibration tends to cause large cable displacement and thus imposes baneful implications upon cables. Therefore, it is essential to utilize several indicators to quantify such vibrations and send instant warnings when they happen. Therefore, this paper proposes a derivative indicator based on discrete numerical differentiation with an O(n) time complexity, thus offering an obvious advantage to the on-time warning. Thereafter, a novel method applying multiple indicators together with various clustering algorithms, i.e., the KMeans and DBSCAN, is used to deal with the abnormal vibration time history of a cable-stayed bridge, which proves both the accuracy and efficiency of such a method.

**KEYWORDS:** *Bridge cable, vortex-induced vibration, derivative indicator, clustering algorithm.*

**1. Introduction**

Known for its frequent occurrence in cable-stayed bridges and suspension bridges, Vortex-induced vibration (VIV) usually brings about large cable displacement and follows detrimental implications. Therefore, it is essential to conceive an efficacious method that can spontaneously recognize VIV and send instant warnings.

Nowadays, the prevalence of Structural Health Monitoring System (SHMS) offers a tremendous opportunity for the big-data-based study of cable vibration. Due to their convenience and relatively low price, accelerometers are widely used in SHMS as the major data resources. The root mean square (RMS) of acceleration time history is then deemed as the prime indicator to quantify the cable vibration intensity. However, more information is deserved to distinguish the VIV from other anomalies, since multiple kinds of abnormal vibrations could cause large-acceleration vibrations. Typically, researchers employed the Fourier transform to obtain either the frequency spectrum or power spectrum, which can be used to analyze the excited modes. The spectrum with a single high peak indicates the occurrence of VIV since this kind of vibration usually comprises only one major vibration frequency [1].

Recently, scholars presented numerous innovative methods to detect VIV from acceleration time history. Among all these methods, the novel algorithm based on the Hilbert Transform (HT) is one of the most prevalent. A composite complex analytic signal, whose real part is the original signal while the imaginary part represents the HT of the original, is introduced into this method. The projection of such a signal on the complex plain reflects the constituent of the vibration, as Dan, D. and Li, H. [2] suggest, the more it resembles a hollow ring, the more exact its single-mode attribute, and thus the more exact the occurrence of vortex-induced vibration. Although the method that employs HT is precise, it is somewhat time-consuming, since based on the Fast Fourier transform, whose time complexity is O(nlogn). To enhance the time efficiency, this paper proposes a derivative indicator based on discrete numerical differentiation, which has an O(n) time complexity, thus obviously lowering the calculative time and bringing about a dependable on-time warning.

Furthermore, since any individual indicator might fail to distinguish VIV from normal vibration due to complicated environmental effects, more indicators should be taken into consideration. Although He, M. et al. [3] claim that KMeans might be the best choice to separate different kinds of vibrations, this algorithm is extremely sensitive to outliers. To overcome these shortages, a method applying the DBSCAN clustering algorithm is used in discriminating different vibrations based on RMS and the derivative indicator, i.e., the hollow coefficient of the derivative analytical signal (HCD). SHMS data of a long-span cable-stayed bridge are analyzed accordingly, and the result proves both the accuracy and efficiency of such a method.

The remaining sections are organized as follows. The methodology of VIV identification is explicated in Sec. 2, where several indicators together with two clustering algorithms are introduced. In Sec. 3, these methods are carried out to identify the VIV occurring in a long-span cable-stayed bridge cable, whose long-time acceleration time history is recorded by SHMS. Finally, conclusions are drawn in Sec. 4.

**2. Methodology**

**2.1. Key Indicators for VIV Recognization**

To identify VIV from acceleration time history recorded by the SHMS, various indicators are demanded. First of all, when VIV occurs on a cable, its vibration is usually much more intense than in normal circumstances. Therefore, the root mean square (RMS) of acceleration time history, which can be calculated by Eq. , is applied to represent the intensity of cable vibration. Generally, the larger the RMS, the more likely a certain kind of abnormal vibration is to occur.

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Moreover, the single-modal property of large-amplitude VIV is taken into consideration by applying the derivative transform, which is defined in Eq , where *y(t)* and *x(t)* represent the transformed signal and the original signal, respectively.

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The derivative analytical signal is then defined as a complex signal *z(t)*, as shown in Eq. , which consists of both the original signal *x(t)* and the transformed signal *y(t)*.

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According to Eq and Eq. , if *x(t)* is a sine function, the trajectory of *z(t)* will be a cylindrical spiral, whose projection in the complex plane is a circle. Moreover, one additional matter worth attention is that the new signal *y(t)* should be normalized since this process introduces a multiplier *ω*, which is the circular frequency of a sine or cosine function.

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| **derivative_ideal_sin**  **(a)** Ideal sine function |
| **derivative_real_sin**  **(b)** sine function with noises |

**Figure 1.** Projection of the derivative analytical signal of the sine function in a complex plain

The projection of the derivative analytical signal of a sine function in a complex plain is shown in Fig 1, where Fig. 1 (a) and Fig. 1 (b) represent the ideal condition and noise-influenced condition, respectively. To quantify the single-modal feature of VIV, the HCD is defined by Eq. , where *R1*and *R2* represent the inner radius and outer radius displayed in Fig. 1 (b).

**2.2. Brief introduction of Clustering Algorithm for sample classification**

2.2.1. KMeans algorithm

The KMeans algorithm might be the simplest and most famous clustering algorithm among all of them. Firstly, a hyper-parameter *k*, which means the number of clustering centroids, should be determined in advance. After that, the algorithm will automatically portion all data points into *k* classes, such that the sum of each point’s distance to its nearest centroid gradually approaches the minimum value. This process might iterate numerous times and the centroids will be dynamically relocated until no data point changes its classification.

2.2.2. DBSCAN algorithm

DBSCAN is an abbreviation of density-based spatial clustering of applications with noise. It can be inferred from its full name that this method is based on the density of data points that distribute in the sample space. To utilize this algorithm, two major hyper-parameters are entailed, i.e., the density threshold and the neighbor radius. One of the most important advantages of DBSCAN is that it can rule out a substantial number of noise and is thus robust to outliers, which is essential when dealing with practical engineering projects that are vulnerable to environmental noises, such as cable VIV detection.

1. **viv identification of a long-span cable-stayed bridge**

**3.1. Description of Data Processing**

In this section, the SHMS deployed in the Tongling Bridge is used as the data source to demonstrate the proposed algorithms. Locating in Tongling City, Anhui province, the bridge is a long-span cable-stayed bridge, whose cables intermittently suffer from VIV. Therefore, this research might help the bridge owner to detect VIV and send instant warnings.

One cable in the Tongling Bridge is applied to explicate the whole process. The original data provided by SHMS is the time history of acceleration within an hour, whose file type is MATLAB’s mat file. First of all, the one-hour continuous time history is divided into several pieces by a time window with a length of 10 minutes and a slide step of 5 minutes, and the RMS of each time interval is calculated. Then, the Fast Fourier Transform follows to secure the frequency spectrum of acceleration. Furthermore, the derivative transform is performed to get the HCD. Finally, the RMS and HCD are considered together by KMeans and DBSCAN to classify VIV and normal vibration.

**3.2. Illustration of Typical VIV Vibration and Normal Vibration**

As mentioned above, each one-hour continuous time history is sliced by a ten-minute time window. It is noteworthy that since the slide step of this time window is five minutes, there is a five-minute overlapping region between each two contiguous time windows. As a result, each one-hour raw data offers eleven samples.

The discrepancy between VIV and normal vibration is remarkable. Fig. 2 shows the ten-minute time history, frequency spectrum, and projections of both the Hilbert analytical signal proposed by Dan, D. and Li, H. [2] and the derivative analytical signal presented in this paper. It is noticeable that the RMS of VIV is much bigger than that in normal vibration. Moreover, the frequency spectrum of acceleration during VIV almost merely comprise one eigenfrequency, while that during normal condition contains multiple modal components. What’s more noticeable, both the projections of the Hilbert analytical signal and derivative analytical signal display a hollow ring and solid circle in VIV and non-VIV circumstant, respectively. In a nutshell, the VIV manifests a strong attribution of large amplitude and approximately unimodal vibration.

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| **normal**  **(a).** Normal ambient vibration | **viv**  **(b).** VIV |

**Figure 2.** Time history, frequency spectrum, projections of the two analytical signals during 10 minutes

**3.3. VIV Identification Using Varied clustering algorithms**

3.3.1. Classification result of KMeans

As mentioned above, RMS is used to represent the intensity of vibration, while HCD is selected to quantify the single-modal degree. To begin with, the manual-labeled result is shown in Fig. 3 (a). The KMeans algorithm is then applied to identify the VIV and non-VIV by classifying the sample points in the HCD-RMS coordinate system into two classes. Displayed in Fig. 3 (b), the diagram indicates a considerable difference between the manual labels and the KMeans classification results that many VIV sample points with an HCD of approximately zero and an RMS ranging from 50 to 65 are misclassified.

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| RMS-HCD  **(a).** Label | RMS-HCD-KMeans  **(b).** KMeans | **RMS-HCD-DBSCAN**  **(c).** DBSCAN |

**Figure 3.** The classification of VIV and normal vibration

3.3.2. Classification result of DBSCAN

Similarly, DBSCAN is also introduced for VIV recognization, and the result is shown. Herein, the neighbor radius is set to 0.075, while the density threshold is set to one-tenth of the total number of samples. It is noteworthy that the DBSCAN classification manifests much more consistency with the manual label by contrast with the KMeans. Therefore, DBSCAN might be the better method for VIV identification.

**4. conclusions**

To detect the occurrence of VIV in bridge cable, two key indicators, i.e., the RMS and HCD, is utilized to extract certain feature from acceleration time history. Drawn in the HCD-RMS coordinate system, the vibration sample points can be divided into two classes by two clustering algorithms automatically. The results prove that the DBSCAN-based VIV-recognization is much more precise compared with that depended on the KMeans. The proposed methods make it possible to achieve real-time warning of VIV in the future.

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