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Cluster analysis of winds and wind-induced vibrations on a long-span bridge based on long-term field monitoring data

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ABSTRACT

In this study on a long-span suspension bridge, the wind and vibration data collected by a long-term monitoring system from the year 2010 to 2014 are used for cluster analysis. An automatic and fast clustering algorithm is employed to recognize the vortex-induced vibrations (VIVs) on the bridge deck in long-term monitoring datasets. The acceleration amplitude (root mean square) and frequency ratio are selected as indicators for the clustering of the VIVs from other vibrations. Cluster analysis is further conducted on the wind speed field of VIV samples, and the results indicate that the nonuniformity of the wind speed along the span-wise direction has a significant influence on the VIV mode. The relationship between the wind speed field and VIV mode is obtained by the clustering with consideration of nonuniformity of the wind speed.

1. Introduction

A large number of long-span cable-supported bridges have been or are being constructed to link the mainland to islands or to link islands to islands all over the world. As the span increases, the bridge becomes more flexible and has reduced damping capability. Therefore, bridges subjected to the wind are more frequently observed to have dramatic oscillations. The vortex-induced vibration (VIV) of the bridge deck is one of the representative wind-induced vibrations, which was observed in many bridges such as Great Belt Bridge (Larsen et al, 2000 [1], Frandsen, 2001 [2]), Tokyo Bay Bridge (Fujino and Yoshida, 2002 [3]), Xihoumen Bridge (Li et al, 2011 [4]) and so on. Although the VIV of the bridge deck is a vibration with a limited amplitude, which does not cause a brittle collapse, it can result in large displacements and discomfort to drivers. Moreover, the VIVs commonly occur within the low wind speed region; therefore, the occurrence probability of a vortex-induced vibration is relatively high, and this results in long-term fatigue damage.

Wind tunnel tests, computational fluid dynamic numerical simulations and field monitoring are the three most powerful tools to study the VIVs of bridges. As modern measurement and structural health monitoring technologies improve, field monitoring plays a critical role in investigating the wind-induced vibration behavior of bridges and has been attracting more and more attention from researchers. Larsen et al. (2000 [1]) have observed the VIVs of the Great Belt East Bridge during the final phases of deck erection, and guide vanes are designed and implemented to mitigate the VIVs of the Great Belt East Bridge. Frandsen (2001 [2]) has simultaneously measured the wind pressure and acceleration of the Great Belt East Bridge. During the field monitoring period, VIVs of the Great Belt East Bridge are observed. It is found that the crosswind VIVs of the Great Belt East Bridge occurred during a smooth flow of low wind speeds (approximately 8 m/s) with a direction nearly perpendicular to the bridge axis. The characteristics of the wind pressure on the surface are obtained, and the correlation between the span-wise pressures become large when a VIV is occurring. Fujino and Yoshida (2002 [3]) have observed that the first vertical VIV mode of a ten-span continuous single steel box-girder bridge (i.e., the Trans-Tokyo Bay Crossing Bridge) occurs with a wind direction within ±20° to the transverse axis of the bridge and a wind velocity of approximately 16–17 m/s. To suppress the vertical mode vibrations of the bridge, a new type of tuned mass damper (TMD) is implemented in the girder. Li et al. (2011 [4], 2014 [5]) have investigated the VIVs of a long-span suspension bridge with a twin-box girder based on long-term field monitoring data.

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In [4,5], the surface pressure distributions of the full-scale bridge, the flow characteristics around the twin-box girder, the vortex shedding frequency, the dynamic responses of the VIVs and the corresponding wind conditions and the mechanism between the VIV and the twin-box girder are discussed in detail. In addition, the field monitoring results are compared using an 1:25 sectional model test. The comparison of the results shows that the section model had higher suction than the full-scale bridge in the separation region, and the Strouhal number is smaller. However, the recognition of VIVs in a measured dataset is manual by choosing samples with larger vibration amplitude than a threshold and then checking the PSD of the acceleration response. The determination of the threshold and the checking rule are very empirical, which is likely to result in wrong recognition. Furthermore, this procedure takes heavy labor cost and efficiency for selecting VIVs is very low. Chen (2013 [6], 2014 [7], [8]) have investigated the crosswind response of tall buildings and flexible structures at wind speed region higher than the vortex lock-in speed, and the Gaussian or non-Gaussian process feature, the peak factor and kurtosis are employed as indicators to distinguish the VIV and buffeting. However, the threshold for distinguishing VIV and buffeting obtained by different researches is different.

In recent decades, the structural health monitoring systems (including the wind and wind effects monitoring systems) have been implemented in many long-span bridges across the world, especially in China (Ko and Ni, 2005 [9]; Li et al, 2006 [10]; Azarbayejani, et al, 2009 [11]; Jang et al, 2010 [12]; Ou and Li, 2010 [13]). The systems provide a great opportunity to investigate the wind characteristics and effects on real bridges based on long-term field monitoring data. Faced with a massive amount of data, how to identify a typical wind-induced vibration and how to utilize data mining to gain new knowledge are two urgent issues for investigating the wind-induced vibrations based on the field monitoring.

In this paper, cluster analysis is adopted to identify the VIVs of the bridge deck and to investigate the relationship between the frequency (mode) of VIVs and the wind speed field. The cluster analysis, which organizes a collection of unlabeled patterns (usually represented as a vector of observations or as a point in a multidimensional space) into clusters based on similar properties, is a powerful tool for exploratory pattern analysis, decision making, and data mining. The variety of techniques for representing data, measuring proximity (similarity) between data elements and grouping data elements have produced a rich assortment of clustering methods. These methods can be broadly classified into four categories: centroid-based (partitioning) methods, connectivity-based (hierarchical) methods, distribution-based methods and density-based methods.

The k-means method (MacQueen, 1967 [14]) is the simplest and most commonly used partitioning algorithm. This method partitions n data points into k clusters, in which each observation belongs to a cluster with the nearest mean, by minimizing the sum of the Euclidean distance between each data point. The k-means method is relatively scalable and efficient for clustering large data sets because the computational complexity of the algorithm grows linearly with the number of data points. However, like other partitioning methods, the k-means method requires some domain knowledge (which unfortunately is not available for many applications) to determine the number of clusters. In addition, the shape of all clusters found by a partitioning method is convex, which is very restrictive.

Hierarchical methods (Sibson, 1973 [15]; Defays, 1977 [16]) create a hierarchical decomposition of the dataset. The hierarchical decomposition is represented by a dendrogram, a tree that iteratively splits the dataset into smaller subsets until each subset consists of only one object. In such a hierarchy, each node of the tree represents a cluster of the dataset. In contrast to the partitioning algorithms, the hierarchical algorithms do not require the number of clusters to be identified beforehand. However, a termination condition has to be defined that indicates when the merge or division process should be terminated. Unfortunately, hierarchical clustering is suffering a challenge in deriving the appropriate parameters for the termination condition.

In the distribution-based methods, the underlying assumption is that the patterns to be clustered are drawn from one of several distributions, and the goal is to identify the parameters of each and the number of clusters. One prominent method is known as the Gaussian mixture model. Traditional approaches to this problem involve obtaining (iteratively) a maximum likelihood estimate of the parameter vectors of the component densities (Jain and Dubes, 1988 [17]). Recently, the expectation-maximization (EM) algorithm has been applied to the problem of parameter estimation (Mitchell, 1997 [18]). The distribution-based clustering methods produce complex models for the clusters that can capture the correlation and dependence between the attributes (features). However, for many real datasets, there may be no concisely defined mathematical model (e.g., assuming a Gaussian distribution is a rather strong assumption about the data).

More recently, density-based clustering, in which clusters with an arbitrary shape can be easily detected, is proposed (Ester, 1996 [19]). In the density-based spatial clustering of applications with noise (DBSCAN) method, one chooses a density threshold, discards as noise the points in regions with densities lower than this threshold, and assigns to different clusters disconnected regions of high density. However, choosing an appropriate threshold can be nontrivial, and finding cluster centers is computationally costly. Fortunately, Rodriguez and Laio (2014) [20] proposed a novel clustering algorithm that uses fast searching. The algorithm finds density peaks based on the idea that the cluster centers are characterized by a higher density than their neighbors and a relatively large distance from other points with higher densities.

In this paper, the 5-year long-term monitoring data from year 2010 to 2014 on the investigated bridge are selected for analysis. The organization of this paper is as follows: First, cluster analysis is proposed to identify the vortex-induced vibrations (VIVs) of the bridge deck. Second, the cluster analysis is employed to investigate the potential relationship between the wind speed field and the frequency (mode) of VIVs.

2. Clustering algorithm

The clustering algorithm proposed by Rodriguez and Laio (2014) [20] is employed for identifying the vortex–induced vibration of the bridge deck in a large amount of monitoring data in this study. In this clustering method, two quantities are calculated for each data point i: the density ρ_i and the distance δ_i (from data point i to the nearest point of higher density). The local density ρ_i of data point i is defined as

$$\begin{aligned} \rho_i &= \sum_j \chi(d_{ij} - d_c) \\ \chi(x) &= \begin{cases} 1 & \text{if } x < 0 \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{1}$$

where d_{ij} is the distance between data point i and j, and d_c is a cutoff distance. $\chi(\cdot)$ is a step function, if the distance d_{ij} between data point i and j is smaller than the cutoff distance d_c, $\chi(d_{ij} - d_c)$ is equal