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Condition assessment of cables by pattern recognition of vehicle-induced cable tension ratio

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ABSTRACT

The stay cables are one of most critical elements for cable-stayed bridges. This paper proposes a machine-learning based condition assessment method for stay cables by using the monitored cable tension force. First, based on the correlation of cable tension response between cable pairs (defined as the two cables at the upriver side and the opposite downriver side in the double cable planes), cable tension ratio is extracted as the feature variable, and the cable tension ratio is defined as the ratio of vehicle-induced cable tension between a cable pair. It is found that cable tension ratio is only related with cable properties and the transverse position of a vehicle over the deck. Vehicles on the bridge naturally cluster themselves into a few clusters that correspond to the traffic lanes, i.e. the vehicles in one lane form a cluster. Consequently, the vehicle-induced cable tension ratio forms the corresponding clusters or patterns. Gaussian Mixture Model (GMM) is employed for modelling the patterns of cable tension ratio, and each pattern (corresponds to a certain traffic lane) is modelled by a mono-Gaussian distribution. The Gaussian distribution parameters of tension ratio are used as condition indicator of stay cables because they are only related to cable conditions (the information of vehicle transverse location is presented in the number of tension ration patterns). The number of patterns which represents the model complexity are determined by Bayesian Information Criteria (BIC), while other parameters of GMM are estimated by using Expectation-Maximization algorithm under the Maximum Likelihood criteria, based on the monitored cable tension force. The cable condition is then evaluated according to the variation in estimated parameters of GMM. It is noted that pre-process of source separation is conducted to make the cable tension ratio independent from vehicle weight, environmental variant, and possible sensor errors. An FE model analysis is carried out to qualitatively illustrate the principle of the proposed method and physical sense of the cable tension ratio.

1. Introduction

Cables, including stay cables and suspenders, are critical and vulnerable types of structural components in long-span cable-supported bridges. From 1970 to 1990, 48% of more than 30 cable-stayed bridges built in mainland China had been reinforced, repaired or even removed due to cable deterioration, and a total average life-span of 11.8 years for 56 bridges was reported [1]. In recent years, more than 10 catastrophic arch bridge accidents were caused by the breakage of suspendors [2–4]. Therefore, there is an urgent need to adopt effective techniques to monitor and assess the condition and serviceability of bridge cables or suspendors. As a result, Structural Health Monitoring (SHM) technologies, which can provide condition information and maintenance suggestions, have attracted the interest of researchers, engineer and managers worldwide, and a number of bridges have been implemented with structural health monitoring systems around the world [1–4].

Because cables are the main supporting components of long-span bridges, cable tension acts as one of the most important structural health indicators, and monitoring the cable tension in a long-term SHM system is critical [5–8]. Two main types [7–9] of monitoring techniques for stay cable tension force have been developed, one is to monitor the strain of a few of steel wires in a cable, the other is to monitor the total cable tension force (including by using the load cells, the accelerometers, and the magnetic flux sensors). The strain gauge can only monitor the strain of wires with strain gauge, while it cannot measure the strain of other steel

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wires and is very difficult to survive during the installation process. The accelerometers and magnetic flux sensors can only monitor the quasi-static cable tension force. The load cell can monitor the time-variant cable tension force; therefore, it is used for condition assessment in this study. However, the raw data from the analysis of cable tension can hardly be used as the sole condition indicator of cables directly because cable tension is also affected by external loading, environmental effects, material deterioration, noise and sensor zero-shift [1]. Therefore, an indicator which is only responsive to cable condition and is independent from external loads, environmental effects and zero-shifting of sensors is needed. A logical way to handle this is to decompose the raw tension data into individual components and treat them individually. The environment effects on cable tension have been investigated [10–12]. However, the vehicle-induced cable tension force, which dominates the variation of cable tension force, has not been comprehensively studied, except for fatigue damage estimation [9].

Since the 1960s, the use of pattern recognition has significantly increased. A number of algorithms have been proposed in applied mathematics, computer science, and many other cross-disciplines and forms a branch of artificial intelligence [13]. Pattern recognition approaches are used for pattern extraction or knowledge discovery from big data [14]. Farrar et al. [15] recognised that vibration-based damage detection is fundamentally one of the main statistical pattern recognition (SPR) problems and can be studied by machine learning methods. Years later, Farrar and Worden [16] outlined the framework of this type of approach as a type of data-driven methodology.

Worden and Manson [17] defined data-driven approaches for damage identification by establishing a model that statistically represents the system, and the model was expressed as a probability density function; they argue that at least three levels of damage identification (i.e., detection, localization, and assessment, the fourth level is prediction) can be addressed by employing this approach. Gul and Catbas [18] proposed a modified algorithm of an auto-regressive model combined with the Mahalanobis distance for outlier analysis, and successfully identified the boundary condition changes while not equally successful in reduced stiffness cases for a laboratory steel grid structure. Figueiredo, et al. [19] developed four different machine learning algorithms (i.e., auto-associative neural network, factor analysis, Mahalanobis distance (MSD-), and singular value decomposition) on their effectiveness in the damage detection of a base-excited frame model under varying simulated operational and environmental conditions, AR parameters are used as input features, and MSD-algorithm proved to be a better choice, the variety of the input dataset has also been emphasized. Yang and Nagarajaiah developed a classification framework based on the sparse representation and compressed sensing for damage identification, modal feature is extracted by complexity pursuit (CP) algorithm and sparsity property of damage is used, the proposed method was argued effective in damage localization and assessment by a laboratory beam structure test [20–22]. Catbas, et al. [23] presented a correlation-based and non-parametric method for damage detection. Figueiredo, et al. [24] proposed a Bayesian approach for damage detection of bridges based on modal frequencies, in which the parameters are estimated by Markov-chain Monte Carlo methods, this approach was validated by identifying the damage done to the Z24 Bridge in Switzerland, and Gaussian distributions are find effective in representing different function conditions.

Pattern recognition algorithms can usually be divided into two categories, i.e., supervised algorithms that require a labelled dataset (i.e., a dataset obtained from structures with known damage/health conditions), and unsupervised algorithms that do not need a labelled dataset (i.e., a dataset obtained from structures with unknown damage/health conditions). However, most of the aforementioned damage detection practices based on pattern recognition are supervised algorithms, meaning that the damage identification is limited to the experimental or simulated conditions [18,19,21] or simple-supported and short-span bridges with known conditions (e.g., the Sunrise Boulevard bridge in Florida [23] and the Z24 bridge in Switzerland [24]). In contrast, unsupervised algorithms are mostly employed for data outlier analysis in civil engineering, as it is difficult to localize and quantify the potential damage [16]. Although successes in damage detection have been reported in the aforementioned studies, damage-insensitive and environmentally sensitive properties and the damage detection aim have narrowed the scope of SHM and limited full use of the monitored data in terms of achieving deep insight into the *in-situ* structure behaviour [25,26].

In this study, the cable tension ratio of a pair of cables is first extracted as a feature variable. We then propose a pattern recognition paradigm for condition assessment of stay cables based on cable tension ratio. Tension ratio patterns are modelled by GMM and each pattern corresponds to a mono-Gaussian distribution. It is found that the GMM parameters are related to cable condition. Therefore, variation in pattern parameters (i.e. GMM parameters) implies the change in condition of stay cables. Pattern number is determined by BIC criterion and other GMM parameters are estimated by Expectation-Maximum (EM) algorithm. Source separation is conducted in pre-processing to obtain the vehicle-induced cable tension force data and eliminate sensor zero-shift error and environmental variation, tension ratio is then calculated. A case study on a real long-span cable bridge is conducted, and an FE model analysis is carried out for a qualitive illustration of the proposed method.

2. Pattern recognition paradigm of the tension ratio

2.1. Definition of tension ratio

In this study, the cable tension ratio, ς, i.e., the ratio of monitored upriver and opposite downriver vehicle-induced cable tension (vehicle-induced cable tension pairs) is defined as the feature of cluster. Supposing that only one heavy truck travels in a certain lane of a cable-supported bridge at a certain time, the vehicle-induced cable tension pair can be written as follows

$$T_{vu} = F\eta_{vu}(x,y) \quad T_{vd} = F\eta_{vd}(x,y) \tag{1}$$

where T_{vu} and T_{vd} represent the vehicle-induced cable tension of the upriver cable and the opposite downriver cable, respectively; F is the equivalent force of the vehicle load under the assumption of equivalent concentrated force of vehicle and the vehicle-bridge interaction can be neglected in long-span bridges [27]; x and y are the longitudinal and transverse vehicle load positions with the concentrated assumption, respectively; $\eta_{vu}(x,y)$ and $\eta_{vd}(x,y)$ denote the cable tension influence surface under vehicle loading, which are functions of structural properties and the load location (x, y) and independent from the vehicle load weight. Moreover, these factors are usually assumed to be independent of x in codes [28]: $\eta_{vu}(x,y) = \eta_{vu}(x)\cdot\eta_{vu}(y)$ and $\eta_{vd}(x,y) = \eta_{vd}(x)\cdot\eta_{vd}(y)$; $\eta_{vu}(x), \eta_{vd}(x)$ form the so-called influence line longitudinally, and $\eta_{vu}(y), \eta_{vd}(y)$ form the influence line transversally (or in another term: the transverse distribution coefficients). Because the longitudinal location x of the vehicle to the cable pair are identical ($\eta_{vu}(x) = \eta_{vd}$) for the cables on the upper river side and downriver side, Eq. (1) yields to Eq. (2) with a noise term b representing the possible model error due to the effects of vehicles on the other traffic lanes, the vehicle-bridge interaction, etc.