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Statistical bridge damage detection using girder distribution factors

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ABSTRACT

A hypothesis testing framework is introduced for bridge damage detection, which enables a rigorous, decision-oriented approach for detection of bridge damage when it exists. A bridge damage detection hypothesis test is developed using girder distribution factors (GDF) under operational, output-only strain monitoring. GDFs are calculated from measured strain data collected during traffic events at the Powder Mill Bridge in Barre, Massachusetts. A sample of GDFs is drawn to establish a baseline over the course of one week, representing the probabilistic behavior of a healthy bridge under normal operating conditions. A new sample can be compared with the baseline at the end of each day, providing a timely and effective operational damage detection method. A calibrated finite element model is used to simulate damaged bridge GDF samples under four damage scenarios. The damaged bridge GDF samples are compared with the healthy baseline sample using the rank-sum test, and the results are employed to develop a damage index capable of alerting bridge owners of potential damage. A simple bootstrap resampling scheme is used to evaluate the probability of issuing a false alarm (Type I error), as well as the likelihood of not issuing an alert when the bridge is damaged (Type II error). A three-dimensional statistical bridge signature is developed to aid damage localization and assessment. Nonparametric prediction intervals corresponding to a baseline signature are generated using the bootstrap method, creating an envelope of possible baseline bridge signatures. When a bridge signature falls outside the baseline bridge signature envelope, damage is detected. Damage was successfully identified for all four artificial damage cases considered. The overall damage detection method is designed to alert bridge owners when damage is detected and to provide a probabilistic tool to aid damage assessment and localization while controlling for both Type I and Type II errors.

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1. Introduction

The American Society of Civil Engineers (ASCE) estimated that approximately 210 million trips were taken per day over structurally deficient bridges in the United States in 2013 [1]. In 2010, the Federal Highway Administration (FHWA) reported the cost of improving the nation's aging infrastructure greatly exceeded baseline spending [2]. Visual bridge inspections are required every two years, but these inspections can often be subjective and inconsistent, as shown by Moore et al. [3]. Structural health monitoring systems can be an effective means of supplementing visual inspections with objective measured data. The probabilistic damage detection method presented herein can be implemented to alert a bridge owner when damage is detected and provide a tool to aid damage assessment and localization.

1.1. Literature review

The live load distribution factor for a bridge is the ratio of the live load applied to each girder when a vehicle crosses the bridge. When a bridge is designed, AASHTO distribution factors are calculated to determine the percentage of the design load to be carried by each girder based on enveloped maximum live loads [4]. These distribution factors are appropriately conservative. The distribution factor can also be calculated using measured strain data. The term Girder Distribution Factor (GDF) is used herein to distinguish the GDF calculated using measured strain data from the AASHTO distribution factor. Ghosn et al. [5] assumed the GDF for identical girders to be the individual girder recorded strain divided by the sum of all girder strains at a transverse location:

$$\mathrm{GDF} = \frac{\varepsilon_i}{\sum_{j=1}^{N} \varepsilon_j} \tag{1}$$

Since the result of (1) represents the percentage of the live load carried by each girder, the sum of the GDFs for a bridge must be equal to 1:

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$$\sum_{j=1}^{N} \text{GDF}_j = 1 \tag{2}$$

This method of calculating GDFs using measured strains has been commonly accepted and is referenced throughout the literature [6–8]. When all girders have the same stiffness, (1) represents the percentage of the live load carried by each girder. When the girders have different stiffnesses, (1) does not represent the true distribution of the live load, but can be thought of as a comparison of girder peak strains relative to other girders. In this form, the GDF is an effective measure of bridge performance and can be used evaluate changes in girder load sharing.

Stallings and Yoo [9] refined the Ghosn et al. [5] method to account for bridges with different interior and exterior girder sizes. This method used the ratio of section moduli to weight the measured strains and calculate the portion of the load carried by each girder. Cardini and DeWolf [8] employed strain data to compute an envelope of acceptable GDFs, noting that a damaged girder would likely produce a GDF below envelope values. Chakraborty and DeWolf [10] used continuous strain monitoring to compute girder stresses during truck events. The cumulative distribution function (CDF) was utilized to show the probability of the measured stress exceeding the design stress. Kim and Nowak [11] measured GDFs under normal truck traffic and used the CDF to comment on trends in traffic patterns. Plude [12] employed GDFs to investigate the observability of various damage cases, using the standard deviation of the GDFs to establish an envelope of acceptable values. Wipf et al. [13] calculated GDFs for ambient and load test traffic on a high-performance steel bridge, finding that measured distribution factors were typically much smaller than AASHTO distribution factors. Kim et al. [14] observed that under very heavy loads, governing distribution factors were reduced, indicating a redistribution of loads to girders further from the most stressed girder. Shenton and Hu [15] used a genetic algorithm to identify the location and severity of damage based on the redistribution of dead load bending moment. Catbas et al. [16] studied the structural response of bridge components under long term monitoring, observing that temperature effects had an impact on overall system reliability.

Data acquisition (DAQ) systems, both long-term and temporary, continue to become more affordable due to advances in technology. Howell and Shenton [17] created an inexpensive and rapidly deployable bridge monitoring system, emphasizing its use in monitoring fatigue life. Whelan and Janoyan [18] developed and tested a wireless sensor network for real time strain monitoring with remote access capabilities. Teixeira et al. [19] used long-term monitoring for a retrofitted orthotropic bridge deck to observe reduced stresses over one year of monitoring.

Follen et al. [20] defined a bridge signature as the "expected response of a bridge structural system to daily traffic as measured by an instrumentation system". Peak strains collected for heavy truck events were used by Follen et al. [20] to develop a nonparametric survival distribution function (SDF) representing the probabilistic behavior of a healthy bridge. Nonparametric prediction intervals were then developed using the bootstrap method, with a bridge signature falling outside of these prediction intervals indicating possible bridge damage corresponding to a particular level of confidence. The work described in this article employs the idea of statistical bridge signatures introduced by Follen et al. [20] and extends their ideas within a statistical decision and hypothesis testing framework to design an effective strategy for bridge damage detection.

1.2. Objective and scope

This research introduces a hypothesis testing framework that enables a rigorous, decision-oriented approach for damage detection on operational bridges. The method targets bridges where single vehicle crossings are common. Rules are presented for extracting data when only one vehicle is crossing the bridge. Two different hypothesis tests for bridge damage detection are developed based on GDFs calculated from measured strain data. A sample of GDFs was drawn to establish a baseline, representing the behavior of a healthy bridge under normal daily traffic. Because the bridge studied is new and is in good condition, a finite element model (FEM) was used to simulate four bridge damage scenarios in order to evaluate the proposed methodology. A FEM is not needed to carry out this damage detection method, and was only used as a substitute for actual data from a damaged bridge. Four levels of damage identification are commonly referenced in structural health monitoring: (1) detection, (2) localization, (3) assessment, and (4) consequence [21]. The proposed two-part probabilistic damage detection method was shown to detect damage, as well as aid damage localization and assessment. In Part I, damage was detected and assessed using a damage index based on the rank-sum hypothesis test statistic. In Part II, a three-dimensional statistical baseline bridge signature envelope was established using a nonparametric probability distribution based on the bootstrap method. Simulated bridge damage was detected, assessed, and partially localized based on whether or not bridge signatures fell outside of the baseline envelope. The two components of the damage detection method were designed to work together to alert bridge owners of potential damage and aid in damage localization and assessment.

The Type I and Type II error probabilities are of critical importance to any damage detection method. In this research, a Type I error corresponds to issuing a bridge damage alert when no damage is present, often termed a false alarm. The more critical Type II error corresponds to not issuing a damage alert when damage is present. An evaluation of both of these errors is central to the development of the overall methodology and distinguishes this research from previous work.

2. Data collection and data quality analysis at the PMB

The Powder Mill Bridge (PMB) is a three-span continuous bridge located in Barre, Massachusetts (Fig. 1). It was constructed in 2009 and is in good condition. The deck cross section is shown in Fig. 2. The bridge is 47 m (154.2 ft) long, with a center span of 23.5 m (77.1 ft) and ends spans 11.75 m (38.6 ft) in length. The bridge is non-skewed and carries two lanes of traffic and a sidewalk. The deck is 200 mm (0.66 ft) thick and is supported by six steel girders, spaced at 2.25 m (7.38 ft) with 732.5 mm (2.4 ft) overhangs. The exterior girders are W920 $\times$ 345 (W36 $\times$ 232) and the interior

Fig. 1. Powder Mill Bridge.

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