DETECTION OF RAILWAY BALLAST DAMAGE UNDER A CONCRETE SLEEPER BASED ON IMPACT HAMMER TEST

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ABSTRACT

This paper focuses on the detection of ballast damage under a concrete sleeper based on the vibration measurement of the in-situ sleeper. The rail-sleeper-ballast system is modeled as a Timoshenko beam on an elastic foundation. Ballast damage reduces the ballast stiffness in supporting the sleeper. This paper reports the modeling of the rail-sleeper-ballast system and the Bayesian model updating of the ballast stiffness distribution under the sleeper utilizing the measured vibration data from an impact hammer test. The accuracy of the identified ballast stiffness distribution depends very much on the level of modeling error and measurement noise. In the proposed method, the Bayesian probabilistic approach is adopted to explicitly address the uncertainties associated with the model updating results. In order to study the feasibility of the proposed method, a segment of a full-scale ballasted track was built and tested under laboratory conditions. The experimental case study results are very encouraging showing that it is possible to apply the proposed method to detect the "region" of ballast damage and estimate the percentage reduction in stiffness. A discussion on the difficulties to be overcome before this approach can be put in real applications is given at the end of this paper.

Keywords: Damage detection, railway ballast, impact hammer test, Bayesian model updating.

1. INTRODUCTION

With the proliferation of high-speed train networks, the safety of railway track systems attracts growing attention. Every year, hundreds of millions of dollars are spent on the maintenance of railway networks. In the last few decades, a lot of studies have been carried out for the damage detection of the track superstructure including the rails, fasteners and concrete sleepers, while the substructure railway ballast has obtained less attention (Selig and Waters 1994). This research is to fill this gap and develop a practical railway ballast damage detection method.

The railway ballast degradation is defined as the ballast damage in this study. When the ballast under the sleeper is damaged, the stiffness of the ballast will be reduced. This will alter the vibration characteristics of the corresponding in-situ concrete sleeper. Therefore, it is possible to detect the reduction in ballast stiffness by monitoring the vibration of the sleeper.

Grassie and Cox (1985) conducted vibration measurements on a rail track with a section of unsupported sleepers. They also built a simple two-dimensional dynamic model to calculate the dynamic characteristic parameters. A Timoshenko beam element was first used to model the

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concrete sleepers, and this model is now widely used. Dahlberg (2008) analytically modeled the dynamic behavior of an in-situ concrete sleeper as a vibrating Timoshenko beam on an elastic foundation. Dahlberg compared the analysis results of the in-situ sleeper to those of the free-free sleeper, it was observed that the effect of ballast is significant for lower modes but its effect is lower as the mode number increases. These results are consistent with the numerical case studies in references (Lam et al. 2010; Lam and Wong 2011; Lam and Wong 2012). Based on the previous research, the rail-sleeper-ballast system is modeled as a Timoshenko beam on an elastic foundation in the proposed project. Hu and Lam (Hu et al. 2012; Hu and Lam 2012) experimentally verified that the Timoshenko beam on an elastic foundation model can represent the dynamic behavior of the rail-sleeper-ballast system in high accuracy. In 2012, Lam (Lam et al. 2012) successfully detect the ballast damage using the vibration of the sleeper. It must be pointed out that references (Lam et al. 2010; Lam and Wong 2011; Lam and Wong 2012; Lam et al. 2012) were based on a deterministic approach. It is clear that the uncertainty induced by measurement noise and modeling error is one of the most difficult problems in such damage detection method. In this paper, this problem will be addressed by probability theories. One of the main contributions of this paper is to modify the Bayesian statistical system identification method (Katafygiotis et al. 2000; Katafygiotis and Lam 2002) in explicitly handling the uncertainty problem in this ballast damage detection problem.

2. PROPOSED BALLAST DAMAGE DETECTION METHODOLOGY

2.1. The rail-sleeper-ballast system model

In this research, an in-situ concrete sleeper is modeled as a Timoshenko beam on a discrete Winkler elastic foundation with stiffness, k_b. The ballast under the sleeper is divided into three equal regions *A*, *B* and *C* (see Figure 1). It is assumed that the ballast stiffness within a given region is a constant and is equal to the stiffness k_b multiples with a dimensionless scaling factor for that region (i.e., θ_A, θ_B, or θ_C). These three parameters are the main uncertain parameters to be identified for the purpose of ballast damage detection. Due to the aging problem, the modulus of elasticity of the sleeper is also uncertain, and a dimensionless factor θ_E is employed to scale its value from the corresponding nominal value in the model updating process. According to the previous research (Lam et al. 2012; Hu et al. 2012; Hu and Lam 2012), the two rails (with rail pads) on the sleeper can be modeled as two different additional masses in the computer model. They are $m_L = \theta_L m_r$ and $m_R = \theta_R m_r$, where m_r is the nominal value of rail mass and θ_L and θ_R are two dimensionless scaling factors, as shown in **Figure 1**.

As a result, a total of 6 uncertain model parameters are considered in the model updating process, and they are grouped into a model parameter vector $\boldsymbol{\theta} = [\theta_A, \theta_B, \theta_C, \theta_L, \theta_R, \theta_E]$. In this study, the nominal values of Young's modulus of concrete sleeper is 38×10^9 N/m^2, mass density of concrete sleeper is 2750 kg/m^3, and the equivalent ballast stiffness and equivalent rail mass are assumed to be 2.0×10^7 N/m^2 and 42 kg, respectively. In the finite element model, the concrete sleeper is divided into 48 elements with equal length along the concrete sleeper.

The formulations of element stiffness matrix, **k**, and mass matrix, **m**, of the Timoshenko beam on an elastic foundation, in reference (Kien 2007) is adopted in developing the finite element model of the rail-sleeper-ballast system:

$$\mathbf{k} = \frac{EI}{l}\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 1 \end{bmatrix} + \frac{\psi GA}{4l}\begin{bmatrix} 4 & 2l & -4 & 2l \\ 2l & l^2 & -2l & l^2 \\ -4 & -2l & 4 & -2l \\ 2l & l^2 & -2l & l^2 \end{bmatrix} + \frac{1}{6}lk_b\begin{bmatrix} 2 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{1}$$

$$\mathbf{m} = \frac{1}{6}\rho l\begin{bmatrix} 2A & 0 & A & 0 \\ 0 & 2I & 0 & I \\ A & 0 & 2A & 0 \\ 0 & I & 0 & 2I \end{bmatrix} \tag{2}$$

where l, E, I, A, ρ denote the element length, the modulus of elasticity, the second moment of area, the cross-sectional area, and the mass density of concrete sleeper, respectively. The shear modulus, G, in Eq. (1) can be expressed as $G = E/(2(1+\nu))$, where ν is the Poisson ratio; and ψ is the correction factor of the cross section of the element. For rectangular cross section in this case, $\psi = 10(1+\nu)/(12+11\nu)$. The element stiffness and mass matrices are used to assembling the system stiffness and mass matrices of the rail-sleeper-ballast system. The modal parameters, such as the natural frequencies and mode shapes, of the system can be easily determined by solving the corresponding eigenvalue problem.

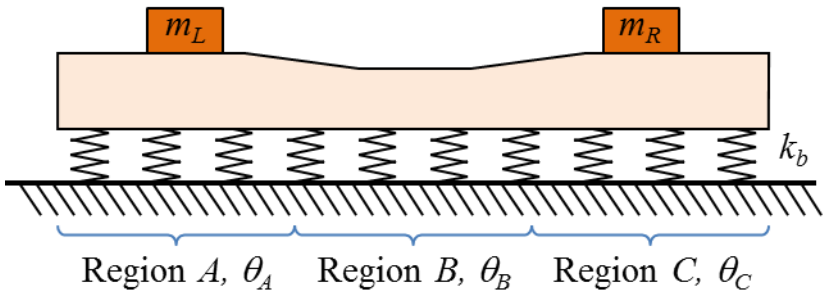

Figure 1: Three discrete regions model of rail-sleeper-ballast system.

2.2. Bayesian model updating

Most deterministic model updating methods aim in solving a minimization problem, in which the discrepancy between the measured and model-predicted modal parameters is minimized with the set of uncertain model parameters as the minimization variables. The objective function of this minimization problem usually consists of two terms. The first term represents the discrepancy between the measured and model-predicted natural frequencies, while the second term represents the mode shape discrepancy. It is very clear that the measurement noise for natural frequency is much smaller than that for mode shape. Therefore, two different weighting factors are usually employed to scale these two terms and so as to show the relatively importance of these two terms in the model updating process. However, there is no commonly accepted and theoretically rigorous method for determining these weighting factors. One of the contributions of this paper is to follow the Bayesian statistical system identification framework (Katafygiotis et al. 2000) in the damage detection of ballast under a sleeper especially the calculation of the weighting factors. Unlike the deterministic approach, which focuses on pin-pointing a solution, the Bayesian approach targets in

calculating the posterior PDF of the set of uncertain model parameters (i.e., $\boldsymbol{\theta}$ in this paper) conditional on a set of measurement and a given class of models. By assuming that the prediction errors of the natural frequencies and mode shapes are random variables that follow the Gaussian distribution, one can use the Bayesian approach to calculate the posterior PDF of $\boldsymbol{\theta}$. By following this direction, one can identify the "most plausible" $\boldsymbol{\theta}$ by maximizing the posterior PDF, and this is equivalent to minimizing the measure-of-fit function (Katafygiotis et al. 2000). Owing to the space limitation, detail formulation of the Bayesian system identification framework cannot be presented in this paper and only the positive-define measure-of-fit function is given below (Vanik et al. 2000):

$$J(\boldsymbol{\theta}) = \sum_{r=1}^{N_m}\sum_{n=1}^{N_s}\left[\frac{\left(\hat{\omega}_r^2(n) - \omega_r^2(\boldsymbol{\theta})\right)^2}{\varepsilon_r^2} + \frac{\boldsymbol{\varphi}_r^T\boldsymbol{\Gamma}^T\left(\mathbf{I} - \hat{\boldsymbol{\psi}}_r(n)\hat{\boldsymbol{\psi}}_r^T(n)\right)\boldsymbol{\Gamma}\boldsymbol{\varphi}_r}{\delta_r^2\left\|\boldsymbol{\Gamma}\boldsymbol{\varphi}_r\right\|^2}\right] \tag{3}$$

where N_s represents the number of sets of modal data, N_m is the number of modes to be considered in model updating, the parameter ε_r is the standard deviation of the squared circular frequencies obtained from the measurement, $\hat{\omega}_r(n)$ is r^{th} measured natural frequency in the nth set of data in rad/s, $\omega_r(\boldsymbol{\theta})$ is the rth calculated natural frequency for a given $\boldsymbol{\theta}$, the selection matrix $\boldsymbol{\Gamma}$ consists of only 1 and 0 that picks the observed degrees of freedom from the model-predicted mode shapes to match the measured ones, $\|\bullet\|$ is the Euclidean norm, $\boldsymbol{\varphi}_r$ is the rth calculated mode shape. Note that $\boldsymbol{\Gamma}\boldsymbol{\varphi}_r$ and $\hat{\boldsymbol{\psi}}_r$ are normalized to have unit norm. The parameter δ_r reflects the uncertainties of the measured mode shapes, which can be computed as:

$$\delta_r^{\,2} = \frac{1}{N_s}\sum_{n=1}^{N_s}\frac{\left\|\hat{\boldsymbol{\psi}}_r(n) - \bar{\boldsymbol{\psi}}_r\right\|^2}{\left\|\hat{\boldsymbol{\psi}}_r(n)\right\|^2} \tag{4}$$

where $\hat{\boldsymbol{\psi}}_r(n)$ is the rth mode shape of the nth set of measurement and $\bar{\boldsymbol{\psi}}_r$ is average mode shape for the rth mode from the N_s sets of data. A smaller value of J in Eq. (3) means a better fit between the measured and calculated modal parameters, and the corresponding $\boldsymbol{\theta}$ is treated as the "most plausible" model for a given sets of measurement. At optimal, the "most plausible" model of the rail-sleeper-ballast system can be obtained. It must be pointed out that the weighting factors $1/\varepsilon_r^2$ and $1/\delta_r^2$ for the natural frequency and mode shape terms are analytically derived from the Bayesian statistical system identification framework.

3. EXPERIMENTAL VERIFICATION

3.1. Experimental setup

A full-scale rail-sleeper-ballast in-door test panel was built in the basement of a factory building at Kowloon Bay, Hong Kong. The ballasted track in the test panel was constructed according to the specification of Hong Kong MTR (MTR 2009). There are seven in-situ concrete sleepers in the test panel, which are imbedded into a 350mm thick granite ballast layer. The size of normal ballast is 50-60mm. Artificial damage was artificially simulated under the left-hand side (2/3 of the sleeper length) of the sleeper by replacing the normal-sized ballast (~60mm) with the small-sized ballast (~15mm). The vibration measurement of the sleeper under this damaged condition was conducted for demonstrating the proposed Bayesian ballast damage detection method.

The list of equipment employed in the experiment is summarized in **Figure 2**. The target sleeper was excited by an impact hammer. The measurement duration is 20 seconds with a sampling

frequency of 6400 Hz through eleven KISTELER-8776A50M3 accelerometers (with sensitivity around 100 mV/g) installed on the top surface along the center line of the concrete sleeper. The sensors were attached vertically upward on the sleeper surface by wax. The vibration signals from the eleven sensors were digitized by four NI-9234 modules, which are connected to the Compact DAQ-9178 chassis (see Figure 2d), with which a maximum of 16 channels can be handled simultaneously.

(a)

(b)

(c)

(d)

Figure 2: (a) KISTELER accelerometers, (b) Cables, (c) Impact hammer, and (d) NI-9234 modules.

3.2. Modal identification

To get an idea about the natural frequencies of the system, the measured time domain responses were transformed to the frequency domain by Fast Fourier Transform (FFT). From the peaks of the spectral density, the natural frequencies of the first four modes of the system were estimated and treated as the initial trials in the modal identification process using MODE-ID (Beck 1978). The first four measured natural frequencies of in-situ concrete sleeper under damaged ballast condition are identified and summarized in **Table 1**. It can be found that the natural frequencies of first two modes are close. It is believed that these two modes are important for damage detection of railway ballast.

Table 1: Measured natural frequencies of the damaged case

	Mode 1	Mode 2	Mode 3	Mode 4
Damaged case (Hz)	59.96	62.63	157.50	405.47

3.3. Bayesian modal updating and ballast damage detection

With the modal identification results, Bayesian model updating was employed to identify the set of "most plausible" uncertain parameters. The Bayesian model updating results are summarized in **Table 2**, $\hat{\theta}_E$ is the scaling factor of the modulus of elasticity, $\hat{\theta}_L$ and $\hat{\theta}_R$ are the factors for the

left and right additional masses, and $\hat{\theta}_A$, $\hat{\theta}_B$ and $\hat{\theta}_C$ are the scaling factors for the ballast stiffness at regions *A*, *B* and *C*, respectively. It is clear that the ballast stiffness on the left (i.e., at Regions *A* and *B*) is smaller than that on the right (Region *C*). This matched the simulated ballast damage. It can be concluded that the proposed method can detect the ballast damage under the sleeper utilizing solely on the vibration data of the in-situ sleeper.

Consider other identified parameters in **Table 2**, the value of the modulus of elasticity is about 67% higher than the nominal value. It must be pointed out that the concrete sleeper is a pre-stressed beam. In the computer model of the rail-sleeper-ballast system, the effect of the pre-stressed force is neglected. This modeling error makes the value of $\hat{\theta}_E$ to be the "equivalent" modulus of elasticity. It is also found that the right mass is about 50% higher than the nominal value but the left mass is equal to zero. The "equivalent" mass of the two rails depends on the leveling of the target and neighboring sleepers. According to the current model updating results, it is believed that the target sleeper may slightly tilted (the right part of the sleeper is slightly higher and the left part of the sleeper is lower). As a result, the mass of the left rail is mainly supported by the two neighboring sleepers.

With the identified "optimal" model, the natural frequencies and mode shapes are calculated and presented in **Figure 3** together with the measured modal parameters. It is very clear that the matching between the measured and updated mode shapes is very good, the dashed line (updated) and solid line (measured) almost overlap with each other. It can be concluded that this class of models is adequate for predicting the modal parameters of the rail-sleeper-ballast system.

Table 2: Updated model parameters when there are 5 uncertain parameters

	$\hat{\theta}_A$	$\hat{\theta}_B$	$\hat{\theta}_C$	$\hat{\theta}_L$	$\hat{\theta}_R$	$\hat{\theta}_E$
Damaged	0.72	0.82	1.03	0.00	1.53	1.67

It is believed that the stiffness of the undamaged ballast is very close to the nominal value, and it corresponds to a scaling factor value of unity. **Figure 4** shows the identified ballast stiffness distribution under the sleeper. It is clear from the figure that the stiffness value at Regions *A* and *B* is lower than unity while that at Region *C* is very close and a little bit higher than unity showing that the ballast under the left 2/3 of the sleeper is damaged. **Figure 4** also shows the damage extent of the railway ballast. At Regions *A* and *B*, the stiffness reductions are about 20% and 30%, respectively.

4. CONCLUSIONS

This paper presents a Bayesian model updating method for the detection of the ballast damage under a concrete sleeper utilizing the measured dynamic responses of the sleeper without lifting up the sleeper. The proposed model updating method provides a theoretical rigorous way in calculating the weighting factors to show the relatively importance of different measured quantities (i.e., the natural frequency and mode shape in this study) in the model updating process.

To verify the proposed methodology, a full-scale in-door test panel was built. Impact hammer test was carried on sleepers with artificial ballast damage. The experimental verification results are very positive showing that the proposed methodology can detect not only the damage location but also the corresponding damage extent.

The proposed ballast damage detection is simple and practical since the modal parameters of the in-situ sleeper can be easily obtained using impact hammer test onsite. However, there are several difficulties to be overcome before this method can be put into real applications. The first problem is related to the modeling of the rail-sleeper-ballast system. Since the ballast stiffness variation along the concrete sleeper is continuous, the discontinuous "jumps" of ballast stiffness at the interfaces between two regions are "artificial". Another problem is the selection of an appropriate model class in capturing the behavior of the rail-sleeper-ballast system for a given set of measurement. In other words, why a 3-region model class is employed but not a 2-region or 4-region model class? Further research is in progress in addressing those difficulties.

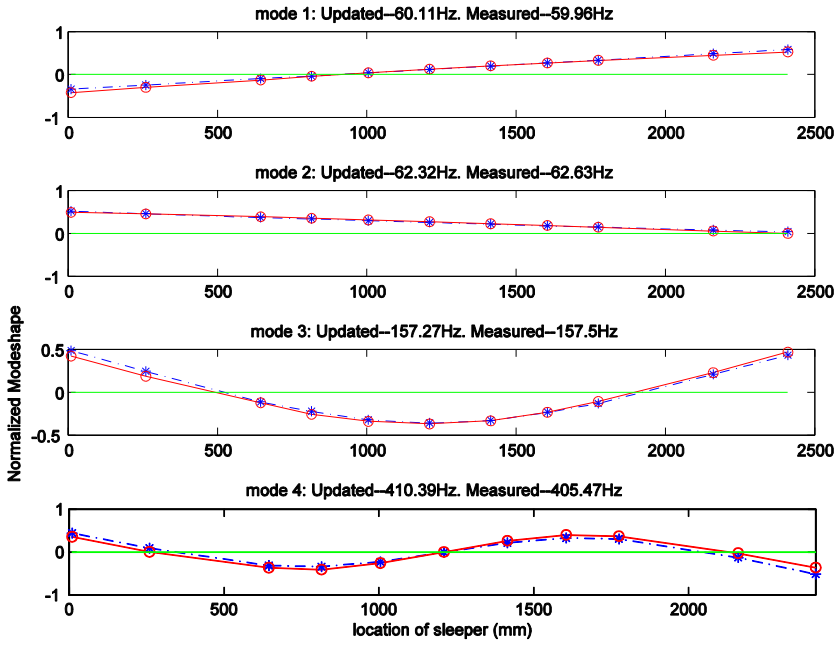

Figure 3: Matching between measured and model-updated modal parameters

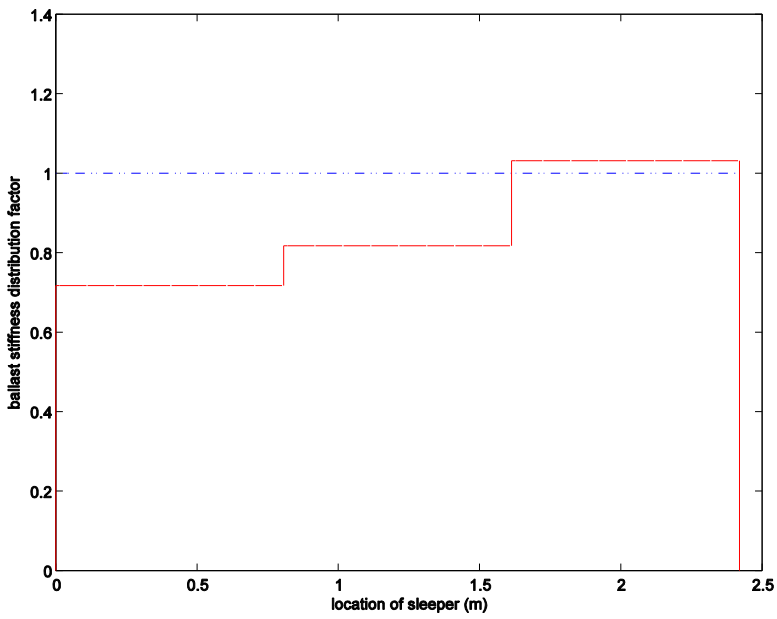

Figure 4: Damage detection of the railway ballast under the sleeper

5. ACKNOWLEDGMENTS

The work described in this paper was fully supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. CityU 114712).

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