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Vehicle Parameter Identification through Particle Filter using Bridge Responses and Estimated Profile

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Abstract

The weight of vehicles driving over bridges needs to be evaluated because the vehicle load potentially causes problems such as fatigue and large vibration. Bridge Weigh-In-Motion systems to evaluate vehicle load by measuring strain response of bridges have been proposed. However, the installation of strain gauges at bridge members are often costly and time consuming, limiting practical applications. This paper investigates the identification of vehicle weight using bridge acceleration response data at different sensor locations through the numerical simulation of vehicle-bridge interaction system. The identified parameters are not limited to the vehicle weight; suspension stiffness and damping coefficients are also identified. A data assimilation technique known as particle filter based on the Bayesian theory is employed to identify the parameters. The time history of the profile is estimated using the same particle filter technique from the dynamic response of a probe vehicle equipped with sensors. The proposed method is shown to have robustness against noises for the mass parameter identification.

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1. Introduction

Vehicle-induced vibration refers to the bridge vibration caused by dynamic forces generated by vehicles passing over a bridge. If it is not well controlled, this unpleasant bridge vibration will cause fatigue problems or even early damage to the bridge. Since this kind of vibration is directly caused by the passing vehicle, the dynamic properties of vehicles, which are reflected by a series of dynamic properties, have a great influence on vehicle-induced vibration. The knowledge of vehicle parameters, especially the mass, is of great importance in at least two ways. The first is that

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the evaluation of real dynamic load is highly dependent on these parameters and valuable information can be provided to the bridge designers for the setting of load. The second is for the purpose of monitoring the vehicle weight on the bridge to see whether the bridge is suffering from overload vehicles that may shorten the working life of road pavement and bridge structure [1]. However, due to the variation of the vehicle-induced load in time and space and the limitation of available bridge response data, this is usually not an easy task. Therefore, how to obtain the vehicle weight as well as other vehicle parameters accurately and efficiently becomes a crucial issue for evaluating the bridge conditions [2].

This problem has drawn much attention in recent years [3-9]. However, it should be noted that the bridge profile is the main vibration source of the vehicle-bridge coupled system. Therefore, having a good knowledge about profile is of great importance. In this paper, a new method is proposed, where the bridge profile is first estimated using a sensor-equipped probe car and then serves as the profile input in the vehicle parameter identification problem. Both the profile estimation and vehicle identification problems are solved using particle filter technique [10-12].

This paper consists of four parts. In section 2, the theory and background of particle filter is introduced. Some concepts are introduced in section 3, including the generation of profile, the methods to calculate vehicle and bridge response and how the vehicle-bridge interaction is considered in this paper. Section 4 shows the details about profile estimation, in which a sensor-equipped vehicle with known parameters is used. The estimated profile in section 4 is then used as the known input to identify vehicle parameters from bridge response. The conclusions are summarized in section 6.

2. Particle Filter

In the particle filter technique, the system is usually expressed in state-space, where a system equation determines the evolution of the state, as shown in Eq. (1)

$$x_{k+1} = f_k(x_k) + w(k) \tag{1}$$

where x_k stands for the state vector that represents the state of the system at time step k. f_k represents the state transition function of the system. $w(k)$ stands for the system error which follows a zero-mean Gaussian distribution.

The observation equation shown in Eq. (2) links the system state and the observation data.

$$y_k = h_k(x_k) + v(k) \tag{2}$$

in which y_k is the measurement vector at time step k and h_k is the measurement function representing the relation between state vector x_k and measurement vector y_k. $v(k)$ is the corresponding observation error also following zero-mean Gaussian distribution.

In Bayesian theory, the objective of estimating the system state is to construct the posterior probability density function (PDF) of the state. This posterior PDF requires information of available observed data. Two stages, known as prediction and update, are necessary to construct PDF. These two procedures are shown in Eq. (3) and Eq. (4) respectively

$$p(x_k \mid y_{1:k-1}) = \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid y_{1:k-1}) dx_{k-1} \tag{3}$$

$$p(x_k \mid y_{1:k}) = \frac{p(y_k \mid x_k) p(x_k \mid y_{1:k-1})}{p(y_k \mid y_{1:k-1})} \tag{4}$$

where $p(x_k|y_{1:k})$ is the conditional posterior PDF of state vector when measurement data up to time step k is known. $p(x_k|y_{1:k-1})$ is called prior PDF which means the measurement data is not available at the current step. The posterior PDF of step k-1 $p(x_{k-1}|y_{1:k-1})$ is assumed to be known. In the update equation, the observed data y_k is introduced to modify the distribution of state from prior PDF to the objective posterior PDF.

Particle filter technique uses a large number of particles to represent the state PDF following a monte-carlo method [10]. In this process, each particle is first passed through the system equation to obtain the prior PDF of next step, which is described in Eq. (3). The objective posterior PDF is calculated through a resampling procedure. When observed data become available, the likelihood of each particle is evaluated and normalised by Eq. (5). A new set of particles are then resampled according to the normalised likelihood. These new particles represent the posterior PDF.