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Drive-by bridge health monitoring using multiple passes and machine learning

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Abstract. This paper studies a machine learning algorithm for bridge damage detection using the responses measured on a passing vehicle. A finite element (FE) model of vehicle bridge interaction (VBI) is employed for simulating the vehicle responses. Several vehicle passes are simulated over a healthy bridge using random vehicle speeds. An artificial neural network (ANN) is trained using the frequency spectrum of the responses measured on multiple vehicle passes over a healthy bridge where the vehicle speed is available. The ANN can predict the frequency spectrum of any passes using the vehicle speed. The prediction error is then calculated using the differences between the predicated and measured spectrums for each passage. Finally, a damage indicator is defined using the changes in the distribution of the prediction errors versus vehicle speeds. It is shown that the distribution of the prediction errors is low when the bridge condition is healthy. However, in presence of a damage on the bridge, a recognisable change in the distribution will be observed. Several data sets are generated using the healthy and damaged bridges to evaluate the performance of the algorithm in presence of road roughness profile and measurement noise. In addition, the impacts of the training set size and frequency range to the performance of the algorithm are investigated.

Keywords: Bridge, Damage detection, Machine learning, ANN.

1 Introduction

Bridges are integral parts of the transport networks worldwide. Globally, bridges are used by a large percentage of the world's population daily where an unexpected closure or collapse of such a structure would cause serious disruptions to the networks. It is obvious that having an understanding of the current structural condition of bridges is of major importance to networks' owners worldwide. As bridges age, damage and deterioration become more present in the structure. However, bridges are most commonly assessed by carrying out a visual inspection. These inspections can give good results when it comes to the immediate structural appearance of the bridge but are oblivious to any internal defects that may be present.

In recent years, more focus has been put on the use of Structural Health Monitoring (SHM) methods for bridge condition assessment. These methods use vibration data gathered from the bridge to extract information relating to the bridge's modal parameters. These parameters consist of the natural frequencies, mode shapes and modal damping which are unique to each bridge. If there is a defect present in the structure, then it should result in a detectable change in the information gathered in these parameters [1].

Currently, the majority of SHM methods applicable to bridges are the approaches that directly instrument bridges. These methods generally require many vibration detection sensors to be installed at intervals all along the span of the bridge [2]. Due to the cost and time required for installation of these sensors, the direct methods are limited to use on larger bridges, and their implementation across whole networks is unfeasible [3]. This is a major constraint to the widespread implementation of direct detection methods, as the majority of bridges globally are of short or medium span. As a result of this, attention has been turned to developing an indirect method for the damage detection of bridges. The use of an indirect method would eliminate the need to install anything directly on the bridge. Measurements and data would be collected by the sensors attached to a vehicle which passes over the bridge. The passing vehicle would be far more efficient to implement across a range of bridges and could be used to cover an entire road/rail network [3].

Yang et al. [4] first proposed the idea of using vehicle measurement for the purpose of bridge monitoring. To date, finding the bridge modal parameters, such as natural frequencies [4], damping ratios [5] and mode shapes [6], has been the main focus of drive-by methods. In addition, some of the methods do not rely on the modal identification and directly process the measured vehicle responses to assess the bridge health condition. For example, Wavelet spectrum of the vehicle response has been employed in a few studies [7, 8].

Many obstacles still remain in the way of the completion of an indirect damage detection method that can be applied consistently under real-life conditions. An approach that is robust to the calculation noise produced by a combination of operational and environmental variables is yet to be produced. These variables include such things as the road surface profile, vehicle speed, and temperature. Road profile with an uneven roughness will result in high amplitude vibrations being introduced into the response spectrum which can mask the changes in natural frequencies of the bridge. As vehicle speed increases, the road profile effects are amplified, the vehicle bridge interaction (VBI) time reduces, and the resolution of the acceleration signal is significantly depleted. Temperature and other environmental effects have been shown to cause a shift in frequency amplitudes due to the associated change in the stress and strain levels in the bridge that accompany climatic changes [9]. A few studies have suggested that the use of multiple runs is a promising approach to tackle these issues [10-13].

Malekjafarian et al. [12] propose a new bridge-damage detection approach using machine learning techniques, combining an Artificial Neural Network model (ANN) and a Gaussian process, to identify healthy bridge condition from unhealthy ones. In this paper, the indirect damage detection algorithm has been proposed by the authors in [12], is further investigated. A numerical finite element model of a bridge is created, and a set number of vehicle crossings of the bridge are simulated at various damage levels. The time domain signal of the VBI is recorded for each crossing. Following this, the signal for each run is used to extract the frequency amplitudes. Fast Fourier Transform (FFT) is performed to extract the frequency amplitudes from the time domain signal. Next, the damage detection algorithm is formulated in two stages. An ANN is trained using a training dataset of velocities and the desired range of frequency amplitudes. Once trained, the ANN is then used to predict the frequency amplitudes when given the vehicle velocity. In the second stage, a Gaussian process is employed to create a damage index which assesses the sensitivity of the algorithm to increasing levels of damage. The predicted data points along the frequency signal are compared to the measured values and a prediction error is found. A larger prediction error in the results corresponds to increased damage being present in the bridge. The network configuration is adjusted, and the results are compared with the aim of finding the optimum arrangement of the network for damage detection. Finally, the VBI response signals are polluted by noise, to represent real-life unpredictable environmental and operational conditions, and the robustness of the network is checked.

2 Finite Element modeling

The VBI shown in Fig. 1 is numerically modelled using finite element (FE). The model that used here is adopt the properties used by Malekjafarian et al. [12] and is a coupled system consisting of a quarter-car model representing the vehicle, and a simply-supported beam model to represent the bridge. The quarter-car system containing two sprung masses and its properties are given in Table 1.

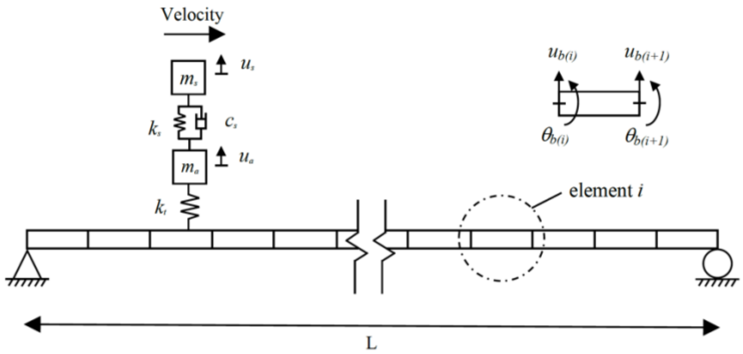

Fig. 1. The VBI.

The bridge is modelled as a succession of a number of beam finite elements. The two nodes of each beam element each have a translational and rotational degree of freedom. The bridge properties are given in Table 2.

Table 1. The vehicle properties.

Properties	Symbol	Value	Unit
Body mass	m_s	9300	kg
Axle mass	m_a	700	kg
Suspension stiffness	k_s	$4x10^5$	N/m
Tyre stiffness	k_t	$1.75x10^6$	N/m
Suspension damping	c_s	10^3	Ns/m

Table 2. The bridge properties.

Properties	Symbol	Value	Unit
Length	L	15	m
Depth	d_b	0.75	m
Width	b	10	m
Mass per unit length	m_b	28,125	kg/m
Modulus of elasticity	E	35,000	N/mm^2
Second moment of area	I	0.35156	m^4
First natural frequency	f_1	4.62	Hz
Second natural frequency	f_2	18.47	Hz
Damping Ratio	ξ	3	%

In reality, road surfaces are never entirely smooth due to requirements for surface friction capabilities, varying aggregate sizes and deterioration. Road profile has also been seen to excite the response signal recorded by the drive-by vehicle resulting in a polluted spectrum from which the bridge frequencies are undetectable. For this reason, a Class A road surface profile has been applied to the FE model based on ISO 8608 to enable the algorithm to be tested in a more realistic environment.

3 The damage detection algorithm

Fig. 2 shows the design of the damage detection algorithm. It uses the fast Fourier transform (FFT) amplitudes of the accelerations measured at the axle to discover the presence of damage in the structure. It consists of two stages. In the first stage, an ANN is trained to predict the frequency amplitudes during the passage of a vehicle over the bridge. In the second stage, the measured FFT frequency amplitudes are compared to the predicted values from the network and the error is used to estimate the presence of damage. The training set is comprised of two inputs and a single target output. The target output is the frequency amplitudes, these are acquired from FFT performed on the acceleration signal of the vehicle. The two inputs are the velocity of the vehicle for a given crossing of the bridge, and a set frequency range to correspond to the target amplitudes.

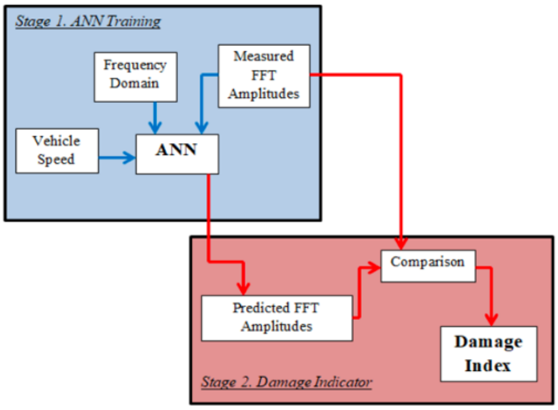

Fig. 2. The damage detection algorithm.

4 Numerical results

4.1 Data generation and damage detection

The numerical VBI model is simulated in MATLAB and is used to gather data for a range of damage levels in the bridge. A training set collected in the healthy condition and monitoring sets for damage levels from 0% damage to 30% damage are formed. Each monitoring set will contain 100 crossings of the vehicle across the bridge with a set damage level. For each crossing, the vehicle speed, between 10 and 15 m/s, and the frequency amplitudes from FFT performed on the acceleration signal are recorded. There is a total of 7 monitoring sets with the corresponding damage level increasing in increments of 5% for each set. The damage is modelled as a crack imposed on the 7th element of the bridge.

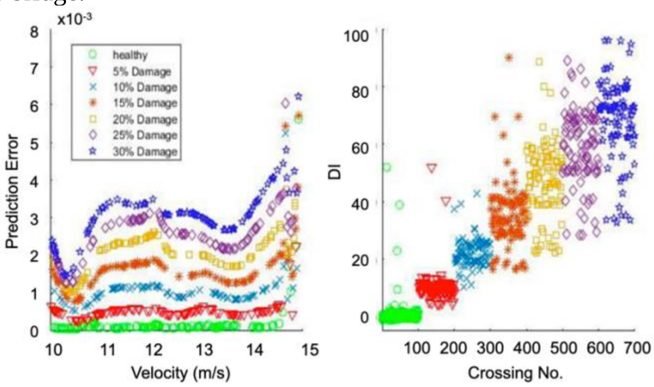

Fig. 3. (a) The prediction error and (b) the damage index (DI).

Fig. 3 (a) shows the prediction errors calculated for the monitoring sets. It can be seen that as the damage level increases, the prediction error also increases. This is reflected in the damage index (DI) in Fig. 3 (b).

4.2 Impact of the training set size

The size of training data set is an important attribute that contributes to the prediction power of the network. The ideal network can predict the exact frequency amplitudes over the given frequency range for any velocity. The training set is initially made up from the vibration data gathered from 100 runs across the bridge. The monitoring data sets are also made up of signals from another 100 random velocities between 10 and 15 m/s. As the vehicle speeds in the new healthy and damaged sets differ from the training set, the prediction errors will vary for different iterations of the crossing within the same damage level scenario. When predicting the signal for the velocities in the monitoring sets the network is required to interpolate from the signals related to the velocities it has been trained from. The more runs that are included in the training set, the more velocities that the training set will be accustomed to. This in turn results in a shorter interpolation required to predict for the velocity sets of the monitoring sets. It can then be deduced that by increasing the size of the training set the ambiguity in the prediction should decrease. In this section, the network is trained using 150 and 200 runs.

Fig. 3 shows the DI for the different numbers of runs in the training part. It can be seen that there is an obvious issue with reliability of the network. The algorithm shows a general sensitivity to an increasing level of damage but for each damage scenario there are a regular number of outliers where the damage index has jumped away from the mean of that set. The effect of such a regular miscalculation for the application of a damage detection algorithm can be of major cost to an economy. An incorrect classification of the deterioration of a bridge, could lead to repairs being planned when in fact the bridge is healthy or, with more serious consequences, vice versa. From Fig. 3, it can be derived that for the training set of 200 runs the number of divergent runs is greatly reduced and the major outliers are completely eliminated. 200 runs will be used as the standard size of the training set for further testing.

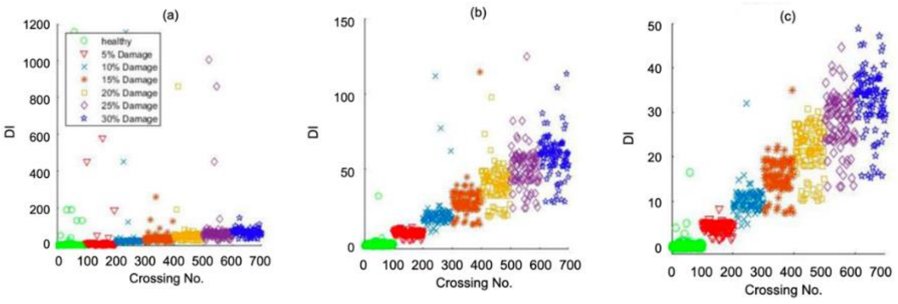

Fig. 3. The damage index for (a) 100 runs, (b) 150 runs and (c) 200 runs.

4.3 Impact of the frequency range

The frequency range to be analysed is a very important factor when designing an algorithm to detect damage once a road profile is introduced. The vibrations imparted on the recording vehicle by the road profile result in a substantial increase in the amount of frequency peaks present in the signal. With an increased number of peaks, and less consistency between the response signals recorded at different speeds, difficulty in associating frequency magnitude shifts to damage rises dramatically. In this section, the frequency range to be analysed by the damage detection algorithm will be adjusted to find the range that gives the optimal sensitivity to damage. The current frequency range being used by the algorithm is the 0-8Hz range. This range was chosen based on the vehicle axle hop frequency of approximately 8Hz.

Fig. 4 plots the prediction error recorded from 10 to 15m/s for each damage scenario for the frequency ranges of 0-5Hz, 0-8Hz and 0-20Hz. It can be seen that the road roughness appears to still have a major influence over the prediction errors adjudged to be present in the monitoring sets in the 0-20Hz range. In contrast to this, the 0-5Hz range shows an obvious positive relationship between the presence of damage and the prediction error recorded. From plotting the damage indexes, it can be deduced that the 0-20Hz range is unsuitable for damage detection and is highly sensitive to the road profile. Whereas the 0-5Hz range offers a highly sensitive solution to an increasing damage level.

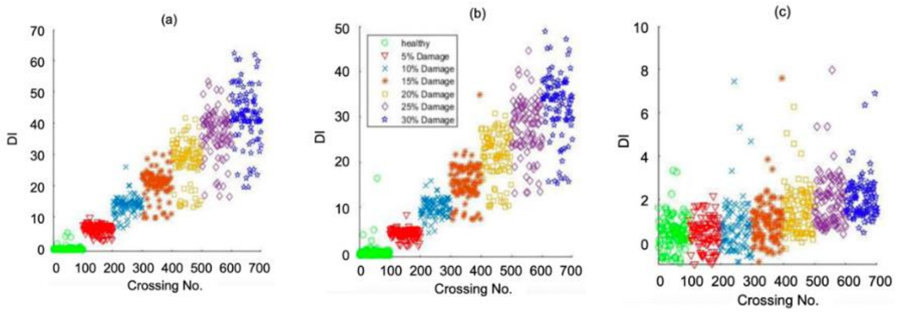

Fig. 4. The damage index when the frequency range used is (a) 0-5 Hz, (b) 0-8 Hz and (c) 0-20 Hz.

4.4 Impact of measurement error

A significant obstacle to the formation of a reliable damage detection algorithm previously, has been the changes to the dynamic behaviour of the structure caused by environmental conditions. In this study, the effects of environmental and operational effects, such as the presence of traffic, are characterised by the presence of white noise. The performance of the algorithm is checked when the recorded acceleration signal has been polluted by a range of noise levels. The acceleration response of the quarter-car with the addition of Gaussian random white noise (GRWN). The robustness of the current network configuration was tested against three levels of measurement noise, 3%, 5%, 10%. The sensitivity of the network to damage and robustness to noise was checked carrying out 100 crossings at each damage scenario, from 0% damage to 30%, and plotting the error on a damage index. The prediction error recorded for every crossing under the increasing noise conditions is plotted in Fig. 5.

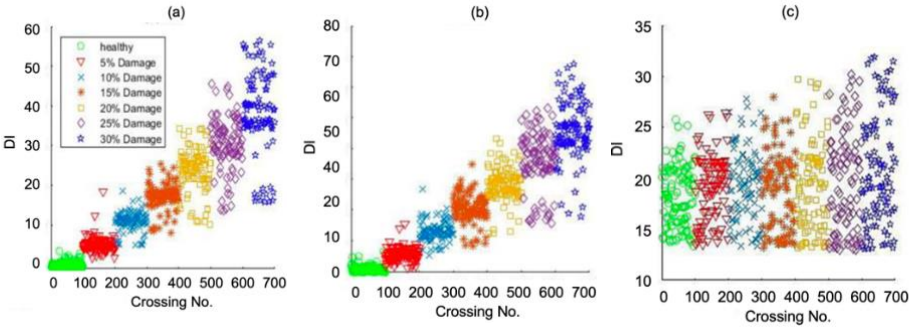

Fig. 5. The damage index when the added noise is (a) 3%, (b) 5% and (c) 10%.

The damage indexes plotted in Fig. 5 confirm that the current algorithm maisntains a high sensitivity to damage even when measurement error up to 5% has been added to the VBI response. As the noise level is increased, the variability of the damage index for each monitoring set increases.

5 Conclusion

This paper studies the feasibility of machine learning for indirect damage detection. An FE model is created and the response of the VBI is recorded. FFT is performed on the time-domain signal and the frequency domain response of the VBI to each crossing of the quarter-car is recorded. The ANN is trained using a set of data recorded for the healthy state of the bridge. The presence of damage is then detected by comparing the measured response for a damaged state with the networks predicted response in the healthy condition and evaluating the level of error present. The sensitivity of the current network configuration to increasing levels of damage is evaluated by the formulation of a damage index. A Gaussian process is adopted to convert the prediction error into the damage index. The size of the training set and the frequency range to be assessed are all adjusted to find the network configuration that gives the optimum performance for damage detection. The performance of the ANN is evaluated measuring the response from a quarter-car model crossing a bridge of length 15m at random speeds of 10-15m/s, with a low roughness surface profile. It is found that the network shows the most sensitivity to damage while remaining robust to the effects of the surface profile when a training set of 200 runs and the frequency range was limited to 0-5Hz.Once the optimal network configuration is chosen, the network is initially examined when 3%, 3% and 10% noise added to the responses. Under these conditions, the algorithm continued to show good sensitivity to the presence of damage up to 5% noise. The variance within the monitoring sets saw a substantial increase due to noise, but the healthy condition always remained well defined and separated from the damaged scenarios. It can be concluded that the ANN shows a good robustness to measurement noise, and the future ability to be trained to differentiate

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