Japan Society of Civil Engineers 2022 Annual Meeting

ESTIMATION OF HIGHWAY BRIDGES' DEFLECTION FROM ACCELERATION MEASUREMENT BY USING A MACHINE LEARNING APPROACH

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1. Abstract

This paper presents a machine learning approach for deflection estimation. This approach overcomes the difficulties in inclination-based deflection estimation, which results in poor estimates when the longitudinal motion of a girder is not negligible. Long-period deflection components corresponding to multiple vehicle passages can be obtained. This method, which requires only acceleration measurement, is validated using the Sampling Moiré Camera (SMC) technique.

2. Introduction

The displacement responses of bridges are important quantities to indicate the structural condition and live loads. Wireless accelerometers have been developed and utilized for possible deflection estimation. For the estimation from acceleration, double integration is not accurate when integration time is long due to slow vehicles or passages of multiple vehicles in series.

A Kalman filter approach incorporating vertical acceleration and inclination can estimate such low-frequency components (Nagayama et al., 2017). However, high-speed vehicles can cause inaccurate estimates due to the bridge's longitudinal motion. The motion influences the inclination measurement and results in poor deflection estimation. The inclination is reasonable only at low speeds reflecting the influence line as shown in Fig-1.

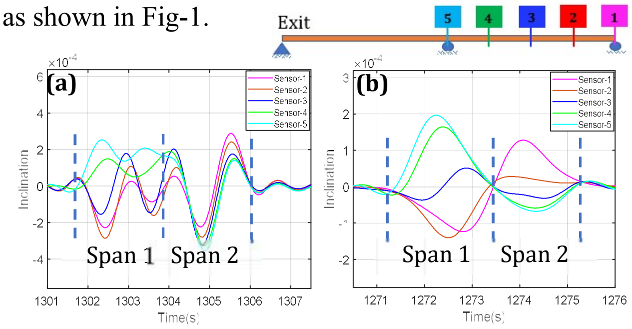
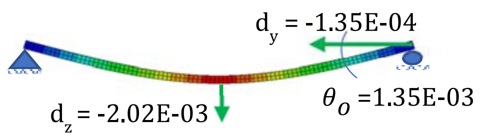


Fig-1: Inclination of a 2-pan continuous bridge at each quarter position of span **a)** 45 km/h and **b)** 90km/h

3. Kalman-filter with Longitudinal Motion Compensation

For the investigation of the speed effect, a simple beam with unit static load at the mid-span is modeled on ABAQUS and vertical displacement, d_z at mid-span and longitudinal displacement, d_y, at the end are determined. Using these results a relation between the dynamic inclination, A_y/g to the static inclination, θ_o is plotted with respect to the drive speed in Fig-2. A_y is the longitudinal acceleration without the gravity component.



$$\frac{d_z}{d_y} = \frac{1}{\beta} \quad => \beta = 0.067 \qquad (1)$$

$$d_y = \beta d_{z0} \sin(\omega t) \qquad (2)$$

$$A_y = -\beta\omega^2 d_{z0} \sin(\omega t) \qquad (3)$$

$$A_{y0} = -\omega^2\beta d_{z0} = -1.35 \times 10^{-4}\omega^2 \qquad (4)$$

$$\hat{\theta} = \theta_0 + \frac{A_y}{g} \qquad (5)$$

$$\frac{\left(\frac{A_y}{g}\right)}{\theta_0} \cong \frac{10^{-1}}{\omega^2} \qquad (6)$$

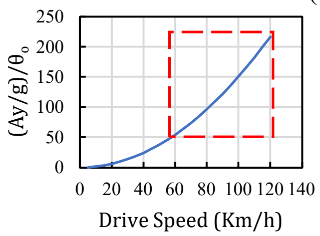


Fig.2: Effect of drive speed on bright inclination response

where, $\hat{\theta}$ is the total inclination including static dead load and dynamic live load, and ω is vibration frequency corresponding to the speed of vehicle.

To overcome this high-speed vehicle induced longitudinal effect from the inclination response, following β-correction is considered.

$$d_y = \beta\, d_z \qquad (7)$$

$$A_y = \beta\, A_z \qquad (8)$$

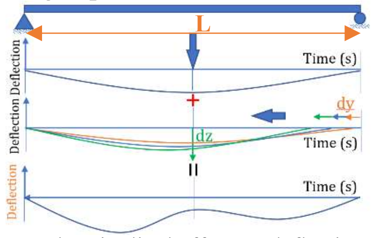


Fig-3: longitudinal effect on deflection

$$A_{y,\ correct} = A_{y,Measured} - (A_{z,Measured\ at\ x = L/2}) \qquad (9)$$

$$\theta = A_{y,correct}/g \qquad (10)$$

The β values are assumed to change linearly from hinge support (exit) to the sliding support (entrance) of the bridge. The inclination estimation is thus compensated for the longitudinal motion and is used as observation variables of the Kalman filter.

4. Determination of β-Coefficients

For the determination of β-coefficients of a target bridge, a genetic algorithm was used the following optimization function was used.

$$F = \left[\sum_{i=1}^{m}\left(D_{KF}^{i} - D_{DI}^{i}\right)^2\right] \cong 0 \qquad (11)$$

where D_{KF} and D_{DI} are deflection estimates by Kalman-filter with **β** corrections and double integration approaches, respectively. Fig-4 shows that the peak deflection matches while off-peak deflection has errors. Even after the configuration of the coefficients, the Kalman filter cannot fully compensate the influence of the longitudinal motion.

5. Proposal of Machine learning Approach

To remove the influence of longitudinal motion, a machine learning approach is proposed.

Keywords: Deflection Estimation, Machine Learning, U-NET, Sampling Moiré Camera (SMC), Highway bridges
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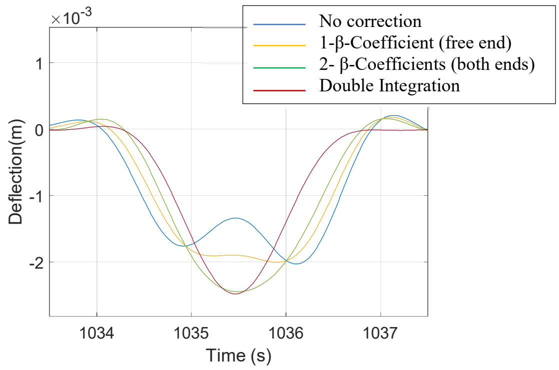

Fig.4: Deflection estimates after β-correction

In this approach, a U-NET-like architecture is used (Weng et al. 2021). The reason of using this architecture is to reproduce the superposition of deflections when multiple vehicles cross the bridge.

The contracting path of this U-NET is consisting of 1-convolution1d layer and 4-sets of down-sampling layers while the expansive path of U-NET is consisting of 4-sets of up-sampling layers and 1-convolutional1d layer. The up-sampling and down-sampling layers are further composed of convolutional1d, ReLu and avgpooling1d layers.

The number of channels for all the layers are set to 32 except for the last convolution1d layer which is equal to size of output i.e., 1. The kernel size and dilation are taken as 5 and 1 respectively. The padding is calculated using Eq. (12) and padding mode is set as 'replicate'.

$$\text{padding} = (k - 1) * d//2 \tag{12}$$

In this network, 8-channels signals of 2000 points are used as an input sample. Among these 8-channels, 1-3 channels have vertical acceleration signal at 1/4L, 1/2L and 3/4L locations, respectively, while channel 4-8 are inclinations responses at 0L, 1/4L, 1/2L, 3/4L and 1L respectively. 1-channel signal of 2000 points corresponding to the deflection at 1/2L (mid-span) is used as a target. L is the span of the bridge.

The model is trained for 100 epochs and batch size is set to 30, which means 100 full passes on the training dataset using a batch size of 30.

The 3000 samples are divided into 3 sub-sets randomly to perform 3-fold cross validation.

6. Preparation of Training Data

For generating the ground truth data, the acceleration signal is double-integrated and all those signals with multiple vehicle passages were removed from the signals. The deflection estimated by double integration of the remaining acceleration signals is employed as the target data.

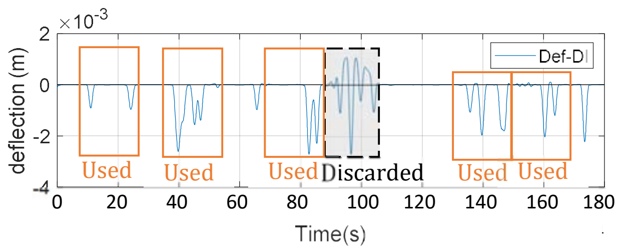

Fig-5: Training data preparation

Each sample consists of 2000 points, i.e., 20s of signals. This data is carefully selected so that a good proportion of training samples should have 2-3 single passings in one sample so that the trained network can also perform accurately for the long signals corresponding to the multiple passings in series as in Fig-5.

7. Results and Validation of the results

The trained network is applied to the input data including the signals corresponding to the multiple vehicle passages in series. Fig-6(a) shows that the machine learning performed well for the signal discarded during the training of the network.

For the validation of the results, field measurements were done using the sampling moiré camera technique developed by Ri et al. (2010).

The comparison between the deflection estimated using the machine learning approach and sampling moiré camera approach shows an RMSE error of 0.67% whereas double integration shows 8.84 % RMS error w.r.t sampling moiré camera deflection.

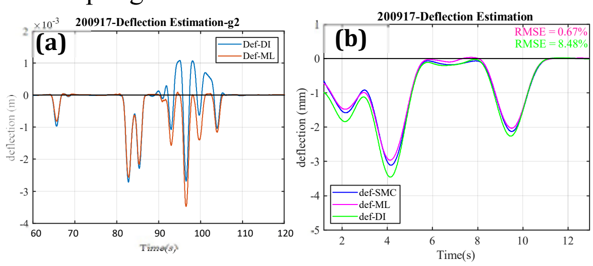

Fig-6: Validation of deflection Estimation

8. Conclusion

Deflection estimation of highway bridge is conducted for the multiple vehicles passing in series with high speed where the existing double integration and Kalman-filter techniques performed poorly.

The results show that the longitudinal effect on girders due to the high-speed vehicles can be overcome using a machine learning approach and deflection with long-period components can be estimated accurately without using the ground truth data from the reference system.

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