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DEVELOPMENT AND APPLICATION OF A BWIM SYSTEM IN A CABLE-STAYED BRIDGE

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Abstract

This study describes the procedures for developing the algorithm for analyzing the signals gathered from the Bridge Weigh-in-Motion (BWIM) system installed in Seohae Bridge as a part of the bridge monitoring system.
Through the analysis procedure, the extraction of information on heavy traffic such as weight, speed, and number of axles from the time domain strain data of the BWIM system was attempted. As one of the several pattern recognition techniques, the Artificial Neural Network (ANN) was employed since it could effectively include dynamic effects and bridge-vehicle interaction.

A number of vehicle traveling experiments with sufficient load cases were executed to acquire the ANN training and/or the test set. The extracted traffic information can be utilized in developing a quantitative database of the loading effect. Likewise, it can contribute to the estimation of the amount of fatigue or current health conditions. The design truck can also be revised based on the database reflecting recent traffic trends.

INTRODUCTION

Alongside the industrial development is the increasing logistics that cause increased amounts of cargo trucks to ply the road. Since each of these trucks poses the dominant load that directly affects the bridges, it is defined as a design live load in the specification and used for designing and maintaining bridges. Since the design vehicle load that is currently presented in road design standards is directly cited from past data used in other countries, it may not be appropriate for domestic situations. In particular, a major error can occur if the standard data is based on those that are several decades old. Therefore, this study attempted to develop a method capable of analyzing the speed, weight, and axle distance of vehicles on the bridge.

The Weigh-in-Motion (WIM) system is currently used for this purpose. As the most widely used system, the fixed WIM system installs the axle scale on the pavement layer of the street to enable trucks to be weighed when they stop or while they are passing it at a low speed. This system is used for controlling truck overload because it can accurately measure the vehicle weight. Still, it tends to generate misleading statistical data from the bridge or pavement engineering viewpoint. A WIM system is typically installed at the highway tollgate or weight control station on a major street that is clearly visible to the truck driver who wishes to avoid it. Weight manipulation or use of a bypass route makes gathering reliable vehicle load data right on the street difficult. Moreover, other data such as the vehicle speed, axle distance, and distance between vehicles cannot be generated.

To overcome such weaknesses, various studies on improving the fixed WIM system have been attempted. As one of the resulting improvements, the high-speed WIM system includes a high-speed axle scale installed on the pavement layer of the street to weigh the cargo trucks plying the road. In other words, they need not be stopped at a certain area for measurement to detect overloading. A loop detector calculates the vehicle speed, axle distance, and distance between vehicles. Since such a high-speed WIM system must precisely reflect the dynamic interaction between the vehicles and road surface (or bridge), development is not easy; in fact, its accuracy is far from satisfactory, thereby requiring other studies for further improvement.

Aside from the methods of measuring the vehicle weight by installing the axle scale on the pavement layer, the Bridge-Weigh-in-Motion (BWIM) system uses a bridge as a scale to measure the weight of the vehicle passing the bridge. Attempted by Moses in the US for the first time in 1979, the BWIM system is a method of weighing the vehicle passing the bridge using the strain signal from the strain gauge installed at the bottom of the bridge girder. In addition to the strain gauge in the bridge girder, the axle detector on the pavement layer is also used to calculate the vehicle speed, axle distance, and distance between vehicles. The influence line is used to calculate the weight. Nonetheless, the primary weakness of this system is its low accuracy. This is because the exclusion of the influence of the dynamic interaction of the bridge and vehicle [1, 2, 3, and 4] produces an error.

Although several studies have proposed the use of the analysis of the characteristics of passing vehicles [5, 6, and 7] and presented the fatigue load model [8] using the accumulated data from the BWIM system with the axle detector, they have focused on the simple span bridge and basically built on the concept of the influence line. Applying the same methods to cable-stayed bridges is difficult considering their structural complexity and longer span length.

This study improved the existing analysis method of using the longitudinal strain and concept of influence line to develop the Free-of-Axle-Detector, Bridge-Weigh-in-Motion (FAD-BWIM) system using the dynamic strain of the lateral floor beam and concrete slab. The system can be applied with greater effect to structures such as a cable-stayed bridge whose slab and girder has moderate stiffness. As one of the pattern recognition methods, the Artificial Neural Network (ANN) was used for signal analysis to incorporate the vehicle-bridge interaction.

MEASUREMENT SYSTEM

Located in Asan Bay on the Seohaean Expressway, the 7,310-km long Seohae Bridge has 6 lanes in either direction. It consists of a cable-stayed bridge (990m), a PSM bridge (5,820m), and a FCM bridge (500m). Since the bridge's monitoring and maintenance systems are described in detail in previous studies [9 and 10], only the measurement system is summarized in Table 1 and Figure 1.

A total of 16 sensors were installed on the 2nd or 3rd lane on the bridge (K1~K8 and S1~S8). Specifically, installation was carried out on two columns at a specific interval considering the time difference due to the speed of the passing vehicle. The 6 strain gauges installed on the floor beam (A1~A6) were used to observe the bending of the floor beam by the passing vehicles and to estimate their weight.

Table 1: Sensor Location and quantity

Location			Quan-tity	Sensor ID*
Dir.	Sec.	Lane		
North-bound	L16	2nd	2	K5, K7
		3rd	2	K1, K3
	L17	1st	1	A3
		2nd	4	K6, K8, A2, P2
		3rd	4	K2, K4, A1, P1
South-bound	L16	2nd	2	S1, S3
		3rd	2	S5, S7
	L17	1st	1	A4
		2nd	3	S2, S4, A5
		3rd	3	S6, S8, A6

* K: concrete-embedment type, A: steel-weld type,
S: concrete-foil type, P: piezo type

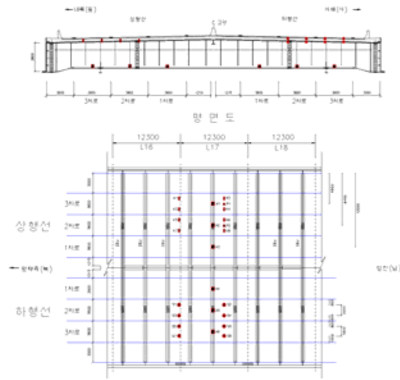


Figure 1. Sensor locations.

VEHICLE TRAVELING TEST

Test Vehicle Traveling Test

Using a test vehicle, a traveling test was performed on the cable-stayed bridge of Seohae Bridge on both southbound and northbound lanes. Loaded and weighed dump trucks with 3, 4, and 5 axles were used. The test vehicles moved between West Pyeongtaek IC and Songak IC of the Seohaean Expressway to pass by the cable-stayed part of Seohae Bridge. The images of trucks passing the bridge were recorded using a camcorder for use as reference for the analysis. Truck speeds were 60km/h, 70km/h, and 80km/h. The test cases were divided by speed and lane. For the test, three vehicles passed the test area serially at a specific interval. Table 2 shows the volume of data generated from each lane. The first test was conducted on September 13 - 15, 2005, with the complementary test performed on October 11 - 12, 2005.

Data from the test were reviewed in real time on the test site and stored in digital media for later analysis. Figures 2 show the typical data of the tests.

Random Vehicle Traveling Test

Since the data from the test vehicles alone could not provide sufficient data for the various weights, axles, and speeds, the generality of the data was improved by measuring the signals generated when random vehicles passed the measurement area. In random vehicle cases, the BWIM system data were compared with the fixed-type axle scale data installed at the Songak and West Pyeongtaek tollgates.

Although general vehicle measurements were performed in the 2005 test, the data quantity was insufficient; thus, a 3rd test of measuring general vehicles was performed on April 26 - 28, 2006. Table 2 also shows the summary of general vehicle data for 2005 (1st and 2nd) and 2006 (3rd) tests.

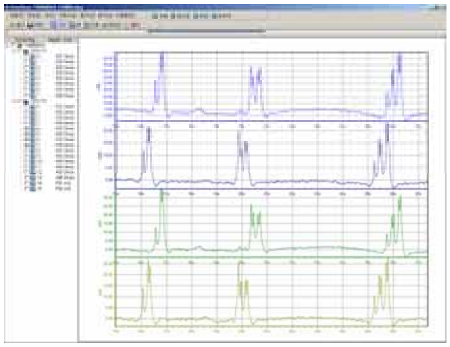


Figure 2. Acquired sample signal (60km/h, 2nd lane, Northbound).

Figure 3. Example of Songak IC Fixed-type axle scale.

Table 2: Test Data on the Test Vehicle (TV) and Random Vehicles (RV)
(Single vehicle cases are enclosed in parenthesis)

Test Lane	2005		2006		Total	
	TV	RV	TV	RV	TV	RV
2nd Northbound Lane	45 (34)	5(5)	-	26(16)	45 (34)	31(21)
3rd Northbound Lane	45 (29)	21(21)	26 (13)	107(64)	71 (42)	128(85)
2nd Southbound Lane	51 (35)	-	-	4(4)	51 (35)	4(4)
3rd Southbound Lane	45 (26)	-	24 (6)	26(20)	69 (32)	26(20)

ALGORITHM FOR EXTRACTING VEHICLE INFORMATION

To develop the algorithm for extracting vehicle information, single vehicle cases from data collected from the procedure described in the previous section were separated as part of preprocessing. A single vehicle case refers to that wherein no signal was generated from other vehicles within 2 seconds of the measurement data section. Therefore, data that included other vehicles preceding or following the measured vehicle or passing at the same time as the measured vehicle were not included for the analysis of the algorithm development. Matlab was used for programming the developed algorithm [(11)].

Identification of the Passing Lane

For the identification of the passing lane, signals from the 16 strain gauges installed on the bottom surface of the concrete slab were analyzed using the ANN. Since 4 strain gauges were respectively installed on the 2nd and 3rd northbound lanes and 2nd and 3rd southbound lanes as shown in Figure 1, the passing lane was easily identified by checking the channel of the signal. The maximum strain values measured from each of the 16 strain gauges were used as inputs for the ANN, which consisted of one hidden layer of ten nodes and one output layer of six nodes.

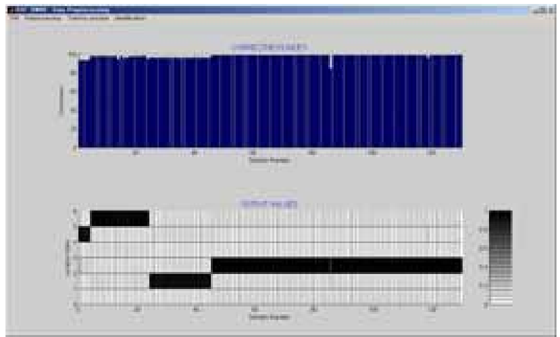


Figure 4. Result of the Identification of the Passing Lane for Random Vehicles.

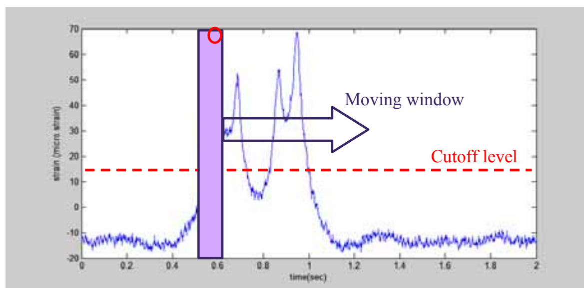


Figure 5. Concept of the Peak Identification Algorithm.

For the ANN training, 120 data sets (30 sets per lane) were used. The performance of the trained ANN was then checked using the test vehicle data and random vehicle data that were not used for training. Figure 4 shows the identification results of the passing lane in 130 data sets. The accuracy of the identification was verified using the correctness index used in a previous study [12]. As shown in the figure, correct identification was achieved in all 130 cases.

Identification of the Number of Axles

The peak identification algorithm was used to estimate the number of axles of the passing vehicles. Figure 5 shows the concept of the peak identification algorithm. As a window of a specific width moved at Δt interval, the position of the maximum value was recorded. A recorded peak position with the same number as the window width was recognized as a peak.

To improve the accuracy of the peak recognition, a cutoff level was assigned such that any peak value falling below such level was not recognized as a peak.

The accuracy of peak recognition depends on the window width and cutoff level. For this study, the window width and cutoff level were set at 20 samples (0.4 sec) and 20% of the maximum value after several trial-and-error settings. The number of axles of test vehicles and random vehicles in the single vehicle cases was estimated. For the test vehicles, 9 inaccurate identifications out of 143 attempts were noted; for random vehicles, 14 errors out of 130 cases occurred. This suggests a general accuracy of more than 90%.

Calculation of the Passing Speed

Once the passing lane is identified using ANN as described in the previous section, the passing speed can be calculated based on the time difference between the signals from two channels and distance between sensors in the channels.

To calculate the time difference from two channels, one channel was fixed, and the other moved along the time axis to find the position where minimum deviation between channels occurred. Once the time difference is identified, the passing speed can be calculated using the distance between sensors (8.2 m) as shown in the following equation and Figure 6:

$$v\,(\text{km/hr}) = \frac{8.2\times10^{-3}\,(\text{km})}{\Delta t\,(\text{sec})}\times 3600\,(\text{sec/hr}) \qquad (1)$$

Calculation of the Total Weight

The dynamic strain signals gathered from the 6 strain gauges installed at the bottom flange of the floor beam were used as the main variable for calculating the total weight. Additional subsidiary variables included the strain of the concrete slab, passing speed of the vehicle, and peak duration.

Unlike the strain on the slab, that of the floor beam is less sensitive to the wheel load of the passing vehicle and consequently more effective when used in calculating the total weight. For the slab strain, a peak value is identified for each axle; the value of the peak is affected not only by the weight of the vehicle axle but also by the vehicle position relative to the sensor. Therefore, the same passing vehicle can yield varying peak values. On the other hand, the strain of the floor beam is dominated by the bending of the floor beam, thereby making the total weight of the passing vehicle the dominant variable.

The strain of the floor beam can be amplified based on the speed of the passing vehicle and its dynamic effect. To reflect the influence of this variable, the speed of the passing vehicle was added to the neural network as an input variable. To address the problem of underestimating the total weight, peak duration as shown in Figure 7 was also added to the input variable to handle vehicles such as a trailer with its long distance between axles.

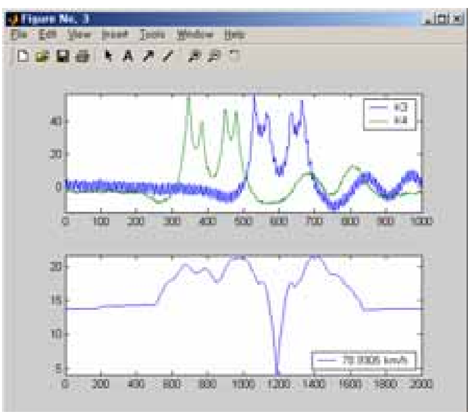


Figure 6. Calculation of the Passing Speed.

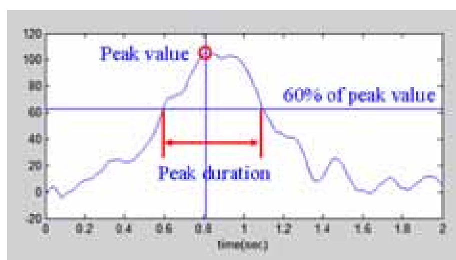


Figure 7. Concept of Peak Duration.

Table 3 shows the final inputs to the weight calculating neural network as a vector of 6 variables. Therefore, the final neural network consisted of an input layer with six nodes, a hidden layer with ten nodes, and an output layer with 1 node. The output node outputs the total weight of the passing vehicle.

The data set for verifying the proposed weight calculation algorithm was prepared based on the 2005 and 2006 tests of the test vehicles and random vehicles passing the 3rd northbound lane (see Table 4). The performances of the network trained with random vehicle data in 2005 (R-05) and that with random vehicle data in 2006 (R-06) were then compared.

Figure 8 shows the test result using the 2005 random vehicle data (R-05). Note that the x axis in the figure denotes the total weight collected from the fixed type axle scale or measuring station, and the y axis, the total weight calculated by the weight calculation algorithm in this study. As shown in the figure, most of the results of T-05 and R-05 in case of training using R-05 fell within the 20% error line (red line). Such calculation error was caused by the error between the total weight calculated by the fixed type axle scale located at the Songak and West Pyeongtaek tollgates and the total weight calculated by the BWIM system. Since the fixed type axle scale has a 5~10% error range, however, the accurate BWIM system error cannot be addressed with these results.

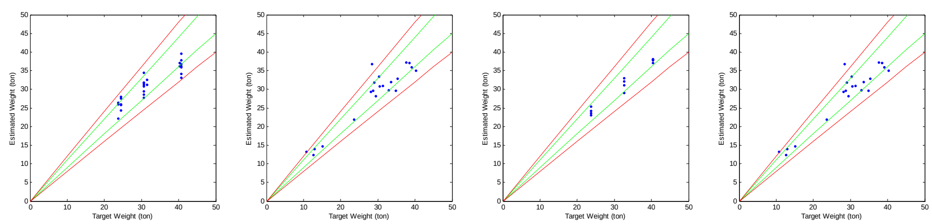
Furthermore, calculating the weight from the 2006 data using the neural network trained with the 2005 random vehicle data tended to underestimate the weight compared to the fixed type axle scale values. In contrast, the neural network trained with the 2006 random vehicle data (R-06) tended to overestimate the weight calculation of the 2005 data. This suggests data changes between 2005 and 2006, possibly due to the seasonal effect and/or deterioration of the sensor's performance over time. Therefore, further studies on testing random vehicles at least every quarter are required to understand accurately the cause of the data change and make a long-term plan. Currently, there is an ongoing study on calculating the axle weight using the floor beam strain.

Table 3: Input variables of the weight calculation Neural Network

Variable	No. of Data
Floor beam strain	3
Passing speed	1
Peak duration	1
Sum of the max. slab strain of each axle	1

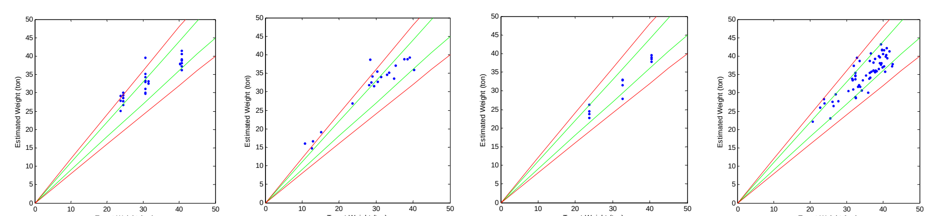
Table 4: Data set used for weight calculation (3rd Northbound lane)

ID	Year Measured	Vehicle Type	No. of Data
T-05	2005	Test Veh.	29
R-05	2005	Random Veh.	21
T-06	2006	Test Veh.	13
R-06	2006	Random Veh.	64



(a) 2005 Test Veh. (b) 2005 Random Veh. (c) 2006 Test Veh. (d) 2006 Random Veh.

Figure 8. Weight Calculation Using the ANN Trained with Random Vehicles in 2005.



(a) 2005 Test Veh. (b) 2005 Random Veh. (c) 2006 Test Veh. (d) 2006 Random Veh.

Figure 9. Weight Calculation Using the ANN Trained with Random Vehicles in 2006.

CONCLUSIONS

This study describes the analysis of the signals from the BWIM system installed as a part of the bridge monitoring system for Seohae Bridge, development of the algorithm to extract passing vehicle information, and results of the data analysis of the vehicle passing test using the developed algorithm.

Based on the results of this study, the following conclusions were drawn:

① For a cable-stayed bridge such as Seohae Bridge, vehicle weight can be calculated within a reasonable error range using the dynamic strain gauge installed on the floor beam.

② The passing lane and passing speed of the vehicle can be accurately estimated using the strain signal from the concrete slab.

③ The passing speed and peak duration were added to the input variables to reflect the influence of the dynamic behavior of the bridge and vehicle and impact of the distance between axles, respectively; thus improving the accuracy of the weight calculation.

④ The weight calculation results of the data based on the measurements in 2005 and 2006 showed a change in the data, which was assumed to be the seasonal effect or deterioration of sensor performance over time. An additional test is ongoing for accurate analysis.

A follow-up study to link the method proposed in this study to the Seohae Bridge monitoring system is in progress. Specifically, the rational vehicle type classification and axle weight calculation considering the distance between axles are being performed. Since this system enables the calculation of the vehicle weight without the driver's notice, the accumulation of more reliable data is expected, unlike in the existing WIM system. Once the automatic weight load calculation program is developed and applied to the field, long-term data accumulation and analysis will enable the provision of useful data for live load design in the future and for bridge performance evaluation.

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