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Application of regression and remote sensing technology for determining sufficiency of contact-based sensors in long-term SHM of civil structures

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Abstract. For structural health monitoring (SHM) of civil structures, one needs to install sufficient sensors for measuring structural responses and influential environmental/operational (E/O) factors. Due to various reasons such as total budgets, weather conditions, structure locations, and monitoring target and duration, it may not be feasible to install all potential sensors. In order to devise and implement an affordable SHM program on large-scale civil structures, this paper proposes a new methodology for verifying the sufficiency of contact-based E/O sensors installed in long-span bridges by benefiting machine learning and spaceborne remote sensing. The main premise of the proposed methodology lies in the fact that structural responses obtained from some products of remote sensing allow civil engineers to investigate the sufficiency of contact sensors and also analyze the impacts of measured and unmeasured E/O factors. Using structural displacement responses obtained from remote sensing and limited measured E/O data from contact-based sensors, a regression model developed from a supervised artificial neural network is designed to evaluate the sufficiency of contact E/O sensors using the R-squared metric under three scenarios. Real-world long-span bridges are considered to testify the proposed methodology using displacement responses and air temperature data. Results demonstrate that the methodology presents an effective and practical strategy for affordable SHM programs.

Keywords: Remote Sensing, Machine Learning, Sensor, Environmental/Operational Data, Displacement Response, Long-Span Bridge

1. Introduction

Long-span bridges are vital civil engineering structures with significant importance in human daily life, transportation, and commerce. Compared to other civil structures and even bridges with short or moderate spans, long-span bridges are significantly susceptible to weak oscillations leading to large vibrations and displacements. On the other hand, such bridge

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types are more sensitive to environmental/operational (E/O) variability attributable to daily and seasonal temperature, wind, and traffic [1-3]. For protecting long-span bridges against any catastrophic incidents, structural health monitoring (SHM) systems in terms of contact and non-contact sensor platforms are often considered to measure influential parameters such as dominant E/O factors and different structural responses. The most applicable contact sensors for SHM of civil structures includes accelerometers, strain gauges, displacement sensors and crack meters, thermocouples, anemometers, humidity sensors, etc. These sensors mainly aim at measuring some prominent structural responses (i.e., acceleration, strain, and displacement) as well as dominant environmental factors (i.e., temperature, wind, and humidity). Although applications of such conventional sensors are prevalent in SHM, recent development in computational algorithms, hardware and software, and data communication has enabled civil engineers to benefit next-generation non-contact sensing systems such as digital cameras [4], smartphones [5], and satellites [6].

Generally, SHM sensing systems can be installed permanently or temporarily. In a permanent sensor installation, as its name indicates, installed sensors act as non-structural elements of bridges that undertake sensing parameters, which are designed to be measured, and transferring sensory data for a long period of operation until those fail. Mostly, this type of sensing requires a sophisticated and automated data acquisition system such as wireless networks. On the contrary, a temporary sensing system is often installed during a short period of time for specific targets. Comparing both systems, one can state that each of them has its own pros and cons. A permanent sensor installation allows civil engineers to measure E/O and structural parameters in a real-time manner and automatically inspect civil structures during long-term monitoring; however, the total costs of permanent sensor deployment may be substantial. Moreover, regular sensor inspections, faulty sensor replacement, utilization of experts, the lack of exploiting some next-generation sensors and measurement techniques are other limitations of this sensing system. On the other hand, although a temporary sensing installation needs less costs and attempts, it may loss some important E/O and structural parameters that can seriously affect civil structures. Therefore, it is essential to consider an operational evaluation and anticipate which sensing system is more beneficial.

Among different sensing systems, spaceborne remote sensing provides the benefit of long-term monitoring programs through images. This is an advantage compared to other non-contact sensing systems, which may not be feasible to capture vision information (i.e., images and videos) during a long period. Typically, some societies such as European Space Agency (ESA) access some products of some satellites. In most cases, synthetic aperture radar (SAR) images are the most useful information for SHM [7-11]. The primary objective is to extract displacements of the civil structure under monitoring via various interferometric techniques [12]. The displacement responses at different areas from SAR images are then used as engineering features for SHM. These features may be caused by operational loadings (e.g., traffic on a long-span bridge), environmental variations (e.g., strong wind, temperature fluctuation and distinction), and natural disasters (e.g., earthquakes, floods, etc.) and man-made hazards (e.g., blasts, accidents, etc.).

Alongside the loads produced by natural disasters and man-made hazards, which are often unmeasurable and sudden, the E/O factors affecting structural responses (i.e., displacements) are measurable. However, some restrictions such as structure locations and environments, operation conditions, weather, SHM targets, and budgets may not allow civil engineers to use all possible sensors for measuring dominant E/O parameters. Regarding long-span bridges, some of these factors may not be influential and there is not an engineering justification to install some specific E/O sensors. In order to devise and implement an affordable SHM program on such complicated structures, it is necessary to develop an effective and efficient sensing system by taking advantage of novel computational methods such as machine learning. It is a branch of artificial intelligence that exploit data and automated algorithms to learn intelligent models that can perform tasks without explicit instructions [13, 14]. Machine learning models are developed for different targets such as classification [15], regression [16], anomaly detection [17], and clustering [18]. To fulfill these objectives, the method utilizes key algorithms from both supervised learning (classification and regression) and unsupervised learning (anomaly detection and clustering).

This paper is intended to suggest an innovative methodology for evaluating the sufficiency of contact E/O sensors mounted on bridges by leveraging machine learning and remote sensing technology. The crux of the proposed methodology lies in regression-based data prediction via a supervised artificial neural network (SANN) and regression accuracy rate in terms of the R-squared (R^2) measure. For sensor sufficiency evaluation, three scenarios are defined by comparing R^2 values of regression modeling with two criteria. On this basis, one can interpret whether the installed contact-based sensors for measuring E/O parameters are sufficient for SHM of the structure under monitoring or other unmeasured E/O factors impacts on structural responses (i.e., displacements) thereby installing or adding further sensors. Several important and large bridge structures are considered to validate the proposed methodology. Results can confirm the methodology effectiveness and practicability.

2. Proposed Methodology

2.1 Regression by Supervised Artificial Neural Network

The SANN is a feedforward fully connected neural network for the regression problem. It entails an input layer, some fully connected (hidden) layers, and an output layer. The initial hidden layer connects to the network inputs, while each subsequent hidden layer links to the layer preceding it. In each fully connected layer, the input data is multiplied by a weight matrix and a bias vector is then added. Following each fully connected layer, an activation function is used, excluding the last one, which has one output; that is, predicted response values. For simplicity, Fig. 1 shows the graphical schematic of a SANN with an input layer, N fully connected layers, and an output layer. To train the SANN, a backpropagation algorithm is considered by defining a loss function in terms of the prediction error between the measured and predicted response data to estimate the weights and bias values. Stochastic gradient descent is also applied to optimize the loss function.

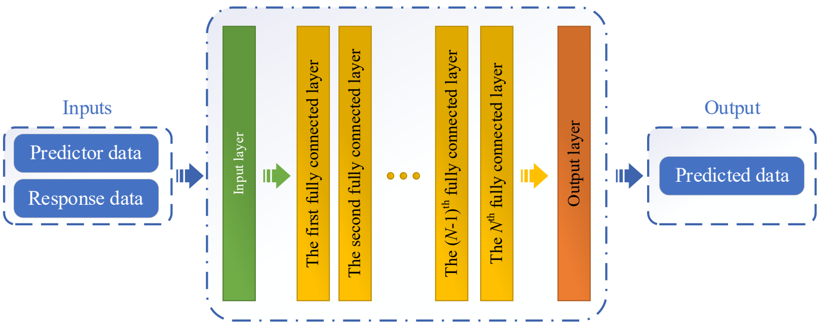

Fig. 1. The graphical schematic of the SANN for the regression problem

Different activation functions can be used to link the network layers. Typically, the most practical functions include rectified linear unit (ReLU), hyperbolic tangent (tanh), sigmoid, and linear functions [19]. On the other hand, the neuron sizes of the fully connected layers are important components of the SANN, which may differ from the input and output layers. Unlike these layers with constant neurons compatible with the input and output dimensions, the sizes of fully connected layers may be variable. Hence, the main hyperparameters of the SANN for the regression problem are the type of activation function, the number of hidden layers (N), and the number of neurons of these layers. In this paper, these items are tuned by Bayesian hyperparameter optimization [20].

2.2 Sensor Sufficiency Metric

Suppose that $\mathbf{x}$ and $\mathbf{y}$ refer to the measured predictor and response data, respectively. In this paper, the predictor is the recorded temperature data obtained from contact-based thermocouples, while the response is the SAR-extracted displacement. Using such information, one can train the SANN to predict the response data $\hat{\mathbf{y}}$. In the regression problem, the R-squared (R^2) metric is a popular and tried-and-tested measure for evaluating the fit quality and accuracy of any regression model. This metric ranges from 0 to 1, where 0 means no fit and 1 means perfect fit [21]. Mathematically, the R^2 function is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{\sum_{i=1}^{n}(y_i - \bar{y})} \tag{1}$$

where $\bar{y}$ denotes the mean of the recorded response data and n is the number of measured and predicted points. To define a sensor sufficiency metric, the R^2 value regarding the measured and predicted response data is compared with two criteria β_1 and β_2, which are scalar values for fixing boundaries. Accordingly, one can derive three scenarios:

1. If $\boldsymbol{R^2 \geq \beta_1}$: This means that the measured predictor is the main reason for variability in the response data. Hence, the installed contact-based sensor for recording the predictor of interest is sufficient.

2. If $\boldsymbol{\beta_2 \leq R^2 < \beta_1}$: This means that although the measured predictor is not the only factor for variability in the response data, it may be influential. Nonetheless, installing more E/O sensors is required to gain other significant factors.

3. If $\boldsymbol{R^2 < \beta_2}$: This means that the measured predictor does not have any strong influences on the response data, while other unmeasured predictors are dominant. For this scenario, the sensor regarding the measured predictor is not necessary and one should install other E/O sensors.

3. Real-World Examples

In order to demonstrate the practicability and performance of the proposed methodology, this section considers three long-span bridges. In these real-world examples, the measured predictor comes from the recorded air temperature measured by contact-based thermocouples. Moreover, the measured response is the displacement samples of some areas of the bridges extracted from limited SAR images of some satellites. Fig. 2 shows the long-span bridges as well as the areas for displacement extraction.

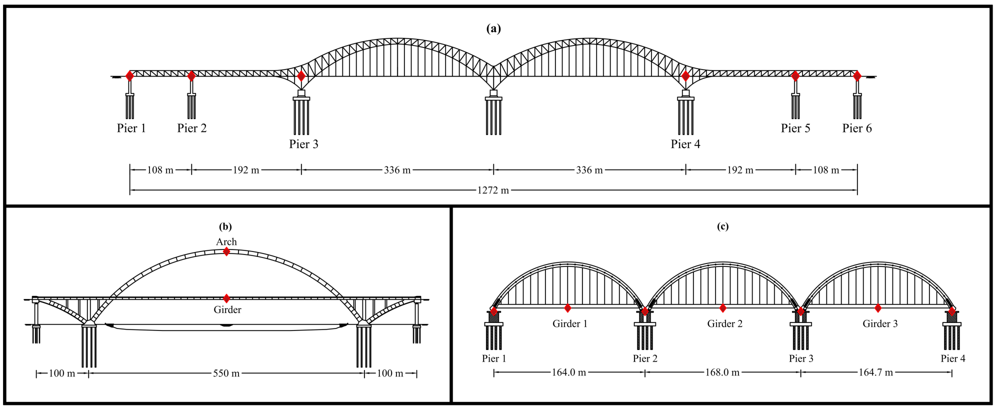

Fig. 2. Real-world examples: (a) Bridge I, (b) Bridge II, (c) Bridge III

The first example (Bridge I) is a steel railway bridge with different long spans constructed in China for high-speed trains [7]. The primary structure of this bridge was made as a continuous steel arch truss. Above the deck, three truss planes are included in the bridge arches and the primary truss is equipped with a welded monolithic joint. During April 25, 2015 to August 05, 2016, 29 SAR images of Sentinel-A1 belonging to European Space Agency (ESA) were used to extract limited displacement responses by using a technique called Persistent Scatterer Interferometry [7]. The responses were extracted at Piers 1-6 as named in Fig. 2(a). Moreover, temperature data during the monitoring period was recorded by a temperature sensor. Fig. 3 displays the recorded temperature data as well as the SAR-extracted displacements of Bridge I.

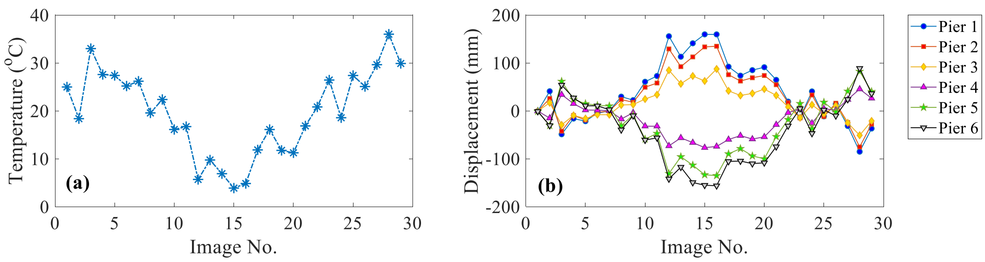

Fig. 3. Data of Bridge I: (a) Temperature, (b) Displacements at Piers 1-6

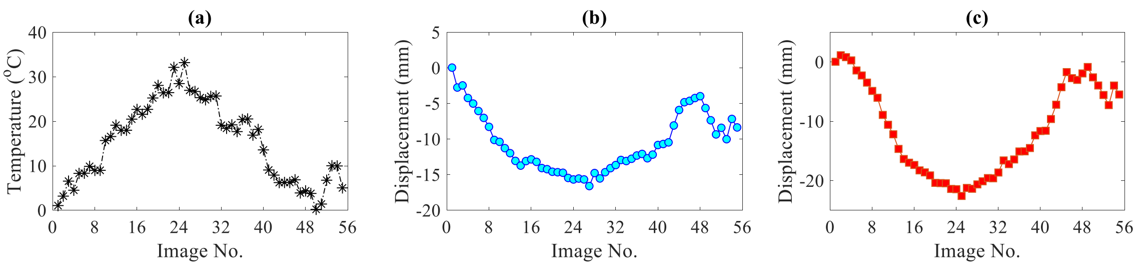

Fig. 4. Data of Bridge II: (a) Temperature, (b) Displacements at the bridge arch, (c) Displacements at the bridge girder

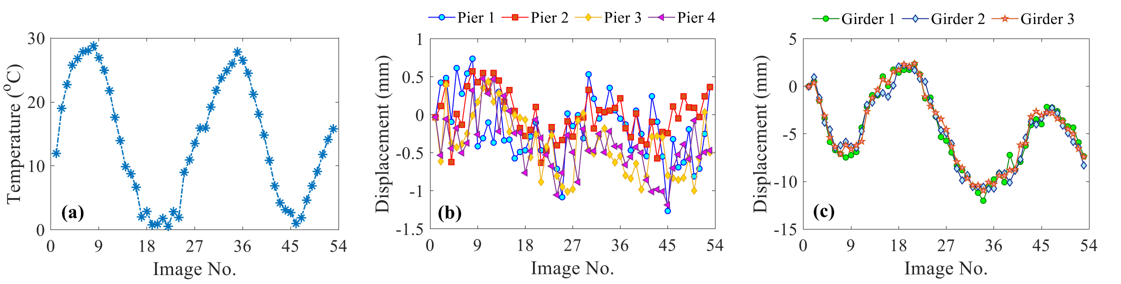

Fig. 5. Data of Bridge III: (a) Temperature, (b) Displacements at Piers 1-4, (c) Displacements at Girders 1-3

The second example (Bridge II) is a steel arch bridge built in China [9]. This structure has a total length of 750m; that is, the main span of 550m and two side spans of 100m, see Fig. 2(b). The main span has a double box-girder form as open steel box-beams, which were joined by open cross-beams. The bridge arch section is a torsionally stiff shape. To compensate the significant horizontal thrust of the main girder, both side span arches, i.e., at their tips, were equipped with horizontal wires. Bridge II was affected by the geological and weather conditions; hence, a field monitoring plan between 2009-2010 was conducted. This plan included the use of 55 SAR images of TerraSar-X was to obtain the displacement responses at the bridge arch and girder sections. Similar to the previous structure, air temperature within the monitoring period was also measured as the main environmental factor. Fig. 4 shows the temperature and displacements of Bridge II.

Finally, the third example (Bridge III) is an arch bridge located in China [9]. The length of the main structure of this bridge corresponds to 496.7m including three key spans of the lengths 164, 168, and 164.7m as shown in Fig. 2(c). Bridge III entails a rigid arch system via a simple supported down bearing flexible tie rod. The deck system consists of a middle cross girder made of prestressed concrete, a longitudinal girder with a T-shape and reinforced concrete for stiffness, and another T-shaped longitudinal girder. After identifying damage patterns, Bridge III was subjected to a long-term SHM program, which made use of 53 SAR images retrieved from Sentinel-A1 to monitor the bridge status between April 01, 2015 to March 27, 2017 [9]. Under this program, a technique called Multi-Temporal Differential Interferometry Synthetic Aperture Radar was applied to extract displacement responses at four pier locations (i.e., Piers 1-4) and three spans (i.e., Girders 1-3). Moreover, air temperature was recorded during the monitoring scheme as the underlying environmental factor. Fig. 5 shows the temperature and displacement responses of Bridge III.

Table 1. Bayesian hyperparameter optimization of the SANN model for Bridge I

Bridge components	*N*	Neuron sizes		
		1st layer	2nd layer	3rd layer
Pier 1	2	3	2	–
Pier 2	3	2	2	3
Pier 3	3	3	1	5
Pier 4	3	2	6	3
Pier 5	2	6	8	–
Pier 6	3	2	6	3

Table 2. Bayesian hyperparameter optimization of the SANN model for Bridge II

Bridge components	*N*	Neuron sizes		
		1st layer	2nd layer	3rd layer
Arch	2	3	2	–
Girder	3	2	2	3

Table 3. Bayesian hyperparameter optimization of the SANN model for Bridge III

Bridge components	*N*	Neuron sizes		
		1st layer	2nd layer	3rd layer
Pier 1	3	42	14	3
Pier 2	3	3	40	2
Pier 3	3	22	2	7
Pier 4	1	48	-	-
Girder 1	1	17	-	-
Girder 2	3	11	8	6
Girder 3	3	14	13	47

The predictor (temperature) and each response are jointed to make the inputs for training different SANN models. For this purpose, the ratio of 80%-20% is considered to generate the training and test data. Initially, Bayesian hyperparameter optimization is applied to determine the numbers of hidden layers (N) and their neuron sizes. In this regard, the initial choices for the layer and neuron numbers are set 3 and 50, respectively. The outputs of hyperparameter optimization in three bridges are presented in Tables 1-3, respectively. For example, the optimized SANN model at Pier 1 of Bridge I requires two hidden layers with three and two neurons for the first and second hidden layers. It should be noted that the activation function ReLU is used without any hyperparameter optimization for the model development.

Table 4. Sensor sufficiency evaluation for Bridge I by the proposed methodology

Outputs	Pier no.					
	1	2	3	4	5	6
R^2	0.9818	0.9753	0.9513	0.9671	0.9578	0.9754
Evaluation	Sufficient	Sufficient	Sufficient	Sufficient	Sufficient	Sufficient

Table 5. Sensor sufficiency evaluation for Bridge II by the proposed methodology

Outputs	Bridge components	
	Arch	Girder
R^2	0.8509	0.9223
Evaluation	Sufficient	Sufficient

Table 6. Sensor sufficiency evaluation for Bridge III by the proposed methodology

Components	Outputs	
	R^2	Evaluation
Pier 1	0.3698	Insufficient – Replace the temperature sensor and add new sensors
Pier 2	0.1759	Insufficient – Replace the temperature sensor and add new sensors
Pier 3	0.0635	Insufficient – Replace the temperature sensor and add new sensors
Pier 4	0.2243	Insufficient – Replace the temperature sensor and add new sensors
Girder 1	0.5098	Insufficient – Retain the temperature sensor but add new sensors
Girder 2	0.4878	Insufficient – Retain the temperature sensor but add new sensors
Girder 3	0.5227	Insufficient – Retain the temperature sensor but add new sensors

The results of the proposed methodology for sufficiency evaluation of the temperature sensors in long-term monitoring of the three bridges are presented in Tables 4-6. For these results, the amount of β_1 and β_2 are set as 0.8 and 0.4, respectively. Accordingly, if $R^2 \geq 0.8$, one can infer that the installed temperature sensor is sufficient and variations in the bridge displacements are primarily due to air temperature. If $0.4 \leq R^2 < 0.8$, this means that the other unmeasured E/O factors affect the displacement responses. Hence, the temperature sensor is insufficient and one needs to add further sensors for recording other parameters such as humidity, rainfall, wind, and traffic. If $R^2 < 0.4$, it can be realized that the temperature has the lowest influence on the displacement responses and it can be ignored it and installed other E/O sensors. Therefore, the outputs in Tables 4-6 reveal that the air temperature is dominant in Bridge I and Bridge II, whereas it is not the major predictor for changes in the displacement responses of Bridge III.

4. Conclusions

This study has presented an innovative application of machine learning and remote sensing technology for an engineering problem regarding SHM of long-span bridges. In SAR-based SHM, structural behavior assessment is based on analyzing displacement responses extracted from SAR images. Since the E/O conditions are the major causes for variability in bridge displacement responses, the choice of all possible contact sensors for recording E/O parameters may be challenging. In this paper, an innovative methodology has been proposed to evaluate sufficiency of contact sensors. The central core of the proposed methodology has concentrated on a SANN model related to the regression problem. Hence, a fully connected layer neural network with the feedforward structure has been developed by training data including the measured predictor and response data. The main objective has been to determine the R^2 value between the measured and predicted response data. Three scenarios have been defined to interpret the sensor sufficiency. The practicability and reliability of the proposed methodology have been verified by three large-scale bridge structures. The results of this study have revealed that the proposed methodology is useful for optimal sensor selection by benefiting the machine learning paradigm.

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