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SENSOR FAULT DIAGNOSIS USING DEEP LEARNING FOR OFFSHORE STRUCTURAL HEALTH MONITORING

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Abstract – A measurement system using strain gauges for structural health monitoring (SHM) was built up. The measurement uncertainty and sensor fault models were studied under a cyclic loading condition emulating the ocean waves. A methodology for sensor fault diagnosis and classification using the Convolutional Neural Network (CNN) deep learning with the images converted from time domain measurement data as the input was investigated.

Keywords: Measurement uncertainty, sensor fault diagnosis, CNN deep learning, structural health monitoring, finite element analysis, offshore structure.

1. INTRODUCTION

Structural health monitoring (SHM) has been utilized for the integrity assessment of marine and offshore structures. Different sensors such as strain gauges and accelerometers are deployed in the SHM system. These sensors operate in harsh marine and offshore environments and are exposed to extreme waves and winds from time to time. The accuracy and fidelity of the measurement data collected from these sensors is a fundamental and critical issue. Most of these sensors are embedded in the structures, which means the classical metrology methodology for sensor fault diagnosis and classification, as well as sensor calibration by shutting down the structure operation or dismantling the structure is not preferrable.

In recent years, data-driven algorithms for sensor fault diagnosis and classification have been explored, which include principal component analysis [1,2], artificial neural networks (ANN) and machine learning [3,4], support vector machine (SVM) classification [5], Bayesian network analysis [6], as well as statistical correlation & generalized likelihood ratio (GLR) [7]. However, these algorithms did not address the accuracy, uncertainty and traceability of the measurement data used in the training process of the models, which made it difficult to justify the fidelity of the data analysis results as required by the relevant standards and guidelines [8].

In this paper, a laboratory scale measurement system using strain gauges for structural health monitoring was built up. Experiments were carried out under a cyclic loading condition emulating the ocean waves. The strain gauge measurement data were cross validated with the virtual measurement data using the Finite Element Analysis (FEA). The measurement uncertainties and sensor fault models were studied. A methodology for sensor fault diagnosis and classification using the Convolutional Neural Network (CNN) deep learning with the images converted from time domain measurement data as input was investigated.

2. STRAIN MEASUREMENT AND SENSOR FAULT

2.1. Strain Measurement

Welded plate joints are the primary structural components in marine and offshore infrastructures. Aligning with the engineering integrity assessment protocols, a laboratory scale measurement system using strain gauges was built up for structural health monitoring of the welded plate joint specimen, which was fabricated utilizing the high strength steel S550. The thickness of the main plate is 40 mm with a width of 40 mm. The total height of the specimen is 440 mm, with the thickness of the vertical attachment equal to 20 mm. The specimen was tested at a Instron model 1334 general material testing machine under three-point bending, with the main plate simply supported at the ends, as shown in Fig. 1. The supported span of the welded plate joint is 300 mm. There were 22 FLAB-1-11-3LJCT strain gauges mounted close to the weld toe along the width of the plate, as marked in Fig. 1. The strain gauges were connected to a unit consisting of the Model 701957 Bridge Heads (DSUB-120 Ω, Shunt CAL, Enhanced Shield) before the measurement data were acquired by a DL850 oscilloscope.

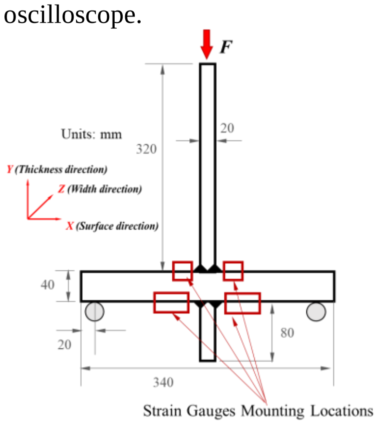


Fig.1 The testing specimen mounted with strain gauges

Ocean waves are caused by energy passing through the water, causing the water to move in a cyclic motion. The regular ocean waves are dominated by the water cyclic motion in a frequency range of 0.0001 Hz~20 Hz [9]. Hence a 5 Hz cyclic loading frequency emulating the ocean waves was applied in the tests of the specimen mounted with the strain gauges. The amplitudes of the cyclic loading force used in the tests were varied from 3 kN to 50 kN. The strain measurements were performed on 5 specimens.

A finite element (FE) model of the welded plate joint specimen was developed. Simulations of the specimen under the physical test conditions were conducted, as displayed in Fig. 2. Virtual strain gauge sensors were defined in the FE model, corresponding to the physical strain gauges mounted at the specimen. The virtual strain measurement results extracted from the FE simulation and strain measurement results by the physical tests were cross validated.

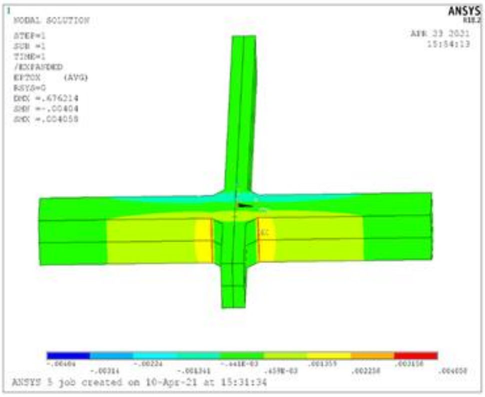


Fig.2 FE simulation of the strain distribution in the specimen

2.2. Measurement Uncertainty and Sensor Faults

The extended uncertainties of the strain measurement data using healthy strain gauges under the emulated ocean waves loading conditions were evaluated as 5%, at the confidence level 95%.

Strain gauge faults were observed in strain measurement of the specimen. The faults of the strain gauge sensor could be classified into three categories: sensor bias, sensor complete failure, and sensor gain. The time domain measurement data of the healthy sensors and fault sensors could be mathematically modelled respectively, as follows,

a) Healthy sensor

$$\hat{x}(t) = x(t) + \mu$$

where $\hat{x}(t)$ is the measurement data, *x(t)* is the expected measurement datal, and μ is the measurement uncertainty.

b) Sensor bias

$$\hat{x}(t) = x(t) + a + \mu$$

where $a \neq 0$, is the measurement bias.

c) Sensor complete failure

$$\hat{x}(t) = b + w$$

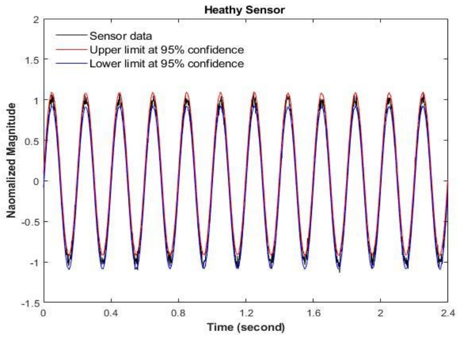
where *b* is a constant, and *w* is a white noise

d) Sensor gain

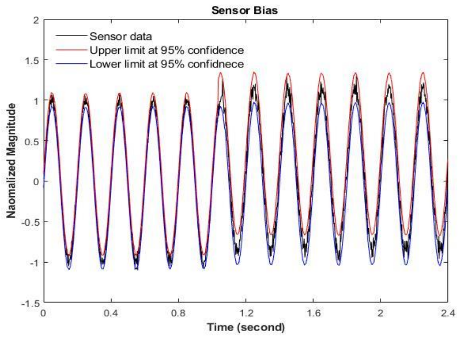
$$\hat{x}(t) = c \cdot x(t) + \mu$$

where $c \neq 1$, is the measurement gain.

The normalized measurement data of the healthy sensors and fault sensors respectively are depicted in Fig.3.



a)



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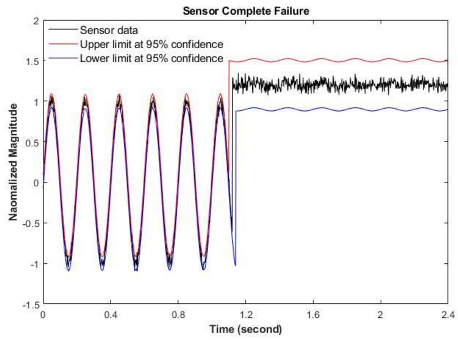
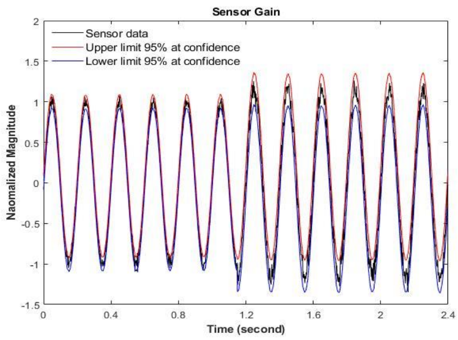


c)



d)

Fig.3 Measurement data of healthy sensors and fault sensors

3. THE CNN METHODOLOGY

3.1. The CNN Methodology

A data-driven sensor fault diagnosis methodology using Convolutional Neural Network (CNN) is proposed. The proposed methodology is capable of extracting features autonomously from the measurement data to perform the sensor fault diagnosis and classification, using the 2-D images converted from the time domain measurement data as the input to the CNN model.

Convolutional Neural Network (CNN) is a Deep Learning algorithm for dataset processing and classification [10]. Specifically, the 2-D CNN is an algorithm widely used in images pattern recognition. The proposed architecture of the CNN model is illustrated in Fig. 4. It consists of two convolutional layers, two pooling layers, a dropout layer, followed by a fully connected layer and a SoftMax layer, and finally, a classification layer for the output. Multiple functional transformations are used for each layer to extract a variety of features. The classification layer has the number of outputs corresponding to the classes of sensor health and fault conditions. The prediction of the classification layer is made on the output probabilities of the SoftMax layer.

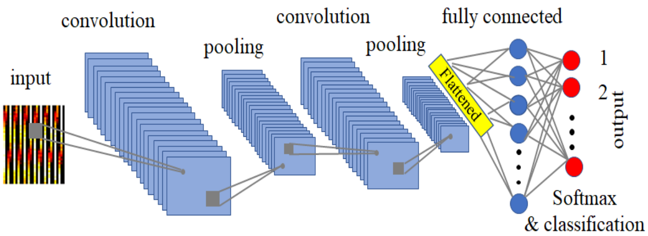


Fig.4 The architecture of the CNN model for sensor fault diagnosis and classification

The convolutional and pooling layers capture the representative features from the images converted from the time domain measurement data for autonomous feature extraction. The CNN model's parameters are learned by the supervised training algorithm. The adaptive moment estimation (Adam) stochastic optimization algorithm is applied to update network's parameters during the training process. Comparing with the similar algorithms, the Adam algorithm is faster in optimizing the learning rate for the CNN parameters, by computing the adaptive learning rates for each parameter of the CNN model using the gradient decay factor and the squared gradient decay factor. After investigating the effectiveness of different configurations and tuning parameters on the classification performance, the architecture of the CNN model is finalized.

3.2. The Data Pre-Processing

A significant amount of measurement data are required in training of the CNN models for the sensor fault diagnosis. In this section, the measurement data of the strain gauge acquired in the physical tests of the specimens, supplemented with the virtual measurement data extracted from the numerical simulations were used. The time domain measurement data were pre-processed by synchronization and standardized normalization. Each time domain data segment consists of 1200 sampling points. Since the measurement data are collected under an emulated ocean wave condition at a single frequency, the sophisticated data pre-processing in time-frequency diagram or histograms is not necessary. Each data segment was directly converted into 40×30 image and categorically labelled before it was used as the input for the CNN model, as displayed in Fig. 5.

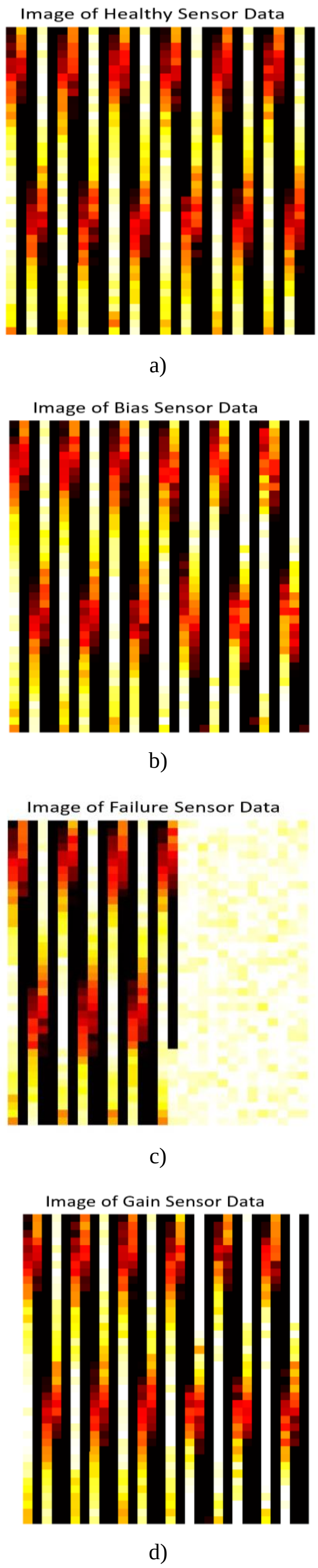


Fig.5 The converted image of the sensor data

4. RESULTS AND DISCUSSION

The Convolutional Neural Network (CNN) is a supervised Deep Learning algorithm. The mature CNN model typically involves three phases: training, validating, and testing.

The pre-processed measurement data were proportionally divided into the training dataset, validating dataset, and testing dataset. The training dataset was used for training the proposed CNN model. The validating dataset was used for assessing the performance of the CNN model in the training process. The training and validating of the CNN model for the strain gauge sensor fault diagnosis were implemented. Fig. 6 displays the progress of the classification accuracy of the CNN model during the training and validating phases. It is found that the final classification accuracy of the CNN model for the training dataset and validating dataset is above 99%.

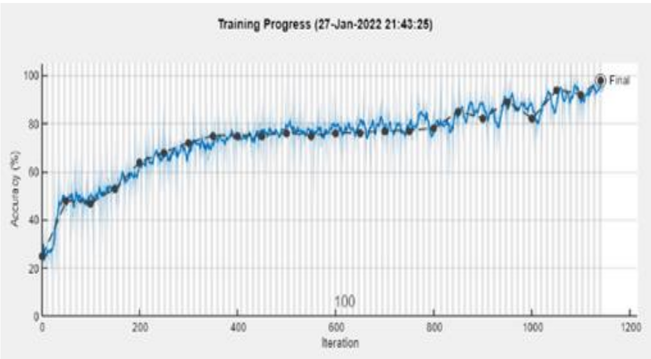
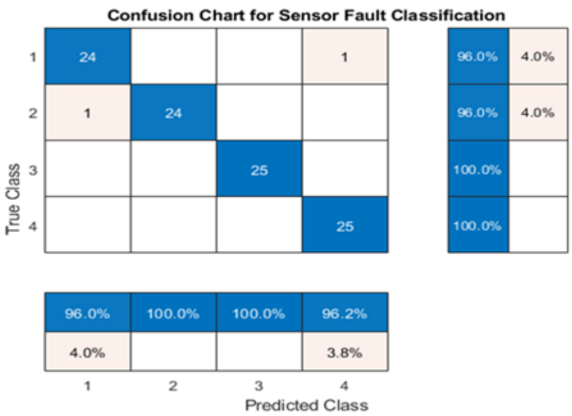


Fig.6 The changing trend of the accuracy in CNN training

The testing dataset was used to test the predication accuracy of the CNN model after the training phase and validating phase were completed. The testing dataset was input into the CNN model to obtain the prediction class and it was compared with the true class of the sensor status. The confusion chart of sensor fault classification using the trained CNN model is listed in Table 1, where the classes from 1 to 4 represent the healthy sensor, sensor bias, sensor complete failure and sensor gain respectively. The CNN model demonstrates excellent accuracy and robustness in sensor fault diagnosis and classification. The prediction accuracy of 96% for the sensor bias (class 2), 100% for sensor complete failure (class 3), and 96% for sensor gain (class 4) are achieved respectively. The prediction accuracy for healthy sensors (class 1) was calculated as 96%.

Table 1 The confusion chart for sensor fault classification using the trained CNN model



5. CONCLUSIONS

The measurements uncertainty and sensor fault models were studied, with a laboratory scale measurement system using strain gauges for structural health monitoring under an emulated ocean wave loading condition.

A data-driven sensor fault diagnosis methodology using Convolutional Neural Network (CNN) deep learning is proposed. The proposed methodology is capable of extracting features autonomously from the measurement data to perform the sensor fault diagnosis and classification, using the 2-D images converted from the time domain measurement data as the input to the CNN model. The CNN model demonstrates excellent accuracy and robustness in diagnosis and classification of sensor faults.

Future work will focus on investigating the applicability limits of the CNN methodology for sensor fault diagnosis and classification for structural health monitoring under the marine and offshore multi-frequency dynamic loading conditions, including sensor drift over the long term.

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