Structural Health Monitoring with Deep Learning

Alex WH Choy

***Abstract*— Electromechanical impedance (EMI) Method is a popular Structural Health Monitoring (SHM) techniques for monitoring the integrity of a mechanical structure. The EMI method is highly sensitivity to small damage. However, it also has a well-known issue, an impedance signal can be changed by other ambient variations. It has the difficulty in damage measurement with the index-based measurement methods, such as RMSD (Root Mean Square Deviation). In this article, we studied the application of the Deep Learning technique to address this issue. An experimental setup was designed for applying the EMI method to monitor the integrity of a metallic structure. The damage classification process has been carried out with a Deep learning tool. This preliminary study demonstrated a very positive result with a reliable measurement with the testing configuration.**

***Index Terms*— Fault diagnosis, Structural Health Monitoring, Electromechanical Impedance (EMI), Deep Convolutional Neural Networks, Deep Learning**

I. Introduction

STRUCTURAL health monitoring is a process to detect damage of an engineering structure with various engineering measurement techniques. The Electromechanical impedance (EMI) Method is one of popular Structural Health Monitoring (SHM) techniques for monitoring the integrity of a mechanical structure by examining the variations in the mechanical impendence of the structure. The variations in the mechanical impedance account the change in structural stiffness, damping and mass caused by the damage in the structure [1]. The EMI method is highly sensitivity to small damage. However, it also has a well-known issue, an impedance signal can be changed by other ambient variations, such as temperature, loading, sensor coupling etc. It causes the difficulty in damage assessment with the index-based measurement methods commonly used in the SHM, such as RMSD (Root Mean Square Deviation), since the human operator is required to interpret a single variated index for assessing damage conditions.

Machine learning is considered as one of the solution to tackle the difficulty of damage assessment in the SHM, which provides the autonomous SHM with the supervised learning. The deep learning has drawn huge amount of attention in the field of machine learning due to its superior performance in visual pattern recognition [2]. However, it has very limited reference in applying the deep learning technique in the SHM application. One of the recent example is from [3], which describes the application of deep learning technique to characterize the damage in the form of cracks on a composite material. However, the paper is mainly focusing on the visual inspection of the structure rather than examining the intrinsic mechanical property of the structure.

In this article, the application of deep learning technique in SHM was studied. An experimental setup was designed for applying the EMI method to monitor the integrity of a metallic structure. A color bar notation has been proposed in this paper to represent the resulted FRF (Frequency Reponses Function) [4] from the EMI measurement. The damage classification process has been carried out with a Deep learning tool. This preliminary study demonstrated a reliable measurement with the testing configuration under different structural conditions.

II. Electromechanical Impedance (EMI) Technique

The EMI technique is based on the mechanical impedance property of a mechanical structure. The integrity of mechanical structure can be evaluated by monitoring the variations in mechanical impendence, which accounts the change in structural stiffness, damping and mass caused by the damage in the structure. The mechanical impedance can be measured by piezoelectric principle, as described as electromechanical impedance (EMI) [4] method.

Under the EMI method, a piezoelectric device, PZT patches are pasted onto a structure specimen. The impedance analyzer will acquire characteristics impendences over a frequency range. The FRF (Frequency Response Function) of the specimen will be created as illustrated in the figure 1.

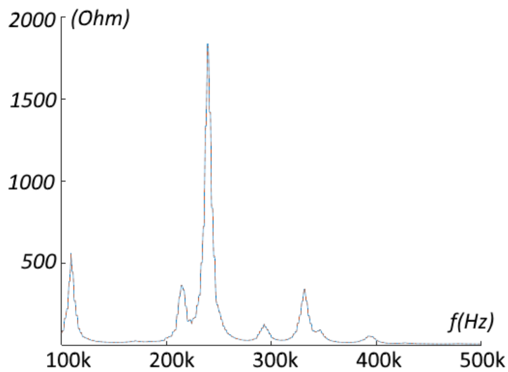

Figure 1 FRF (Frequency Response Function)

In the EMI-based SHM, the key indicator of damage is the change in the real part of the impedance of the PZT patch [4]. The status of a structure can be assessed by monitoring the electrical impedance and comparing it to a

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baseline (the reference condition) measurement for a specified frequency range. One of the popular damage assessment techniques is the root mean square deviation (RMSD) [5]. The RMSD index is presented as follows:

$$RMSD = \sum_{i=1}^{n} \sqrt{\frac{\left[\mathrm{Re}(Z_{i,1}) - \mathrm{Re}(Z_{i,2})\right]^2}{\left[\mathrm{Re}(Z_{i,1})\right]^2}}$$

where RMSD represents the damage metric, $Z_{i,1}$ is the impedance of the PZT measured at healthy conditions, and $Z_{i,2}$ is the impedance for the comparison with the baseline measurement at frequency interval *i*. As discussed, the reliability of the impedance-based method would be affected by different working environmental conditions. The shift of Impedance Frequency Spectrum will cause unreliable damage detection result, particularly applying 'Root Mean Square Deviation' (RMSD) detection technique.

III. Issues of RMSD technique

An experimental setup was designed for applying the EMI method to monitor the integrity of a metallic structure as illustrated in figure 2.

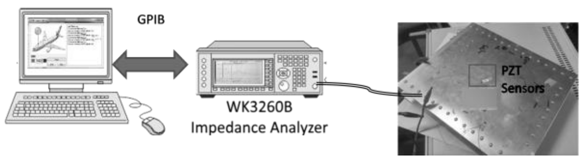

Figure 2 Measurement Equipment setup

The Structural variation was artificially introduced by attaching a mass [7] with an aluminum structure as illustrated in figure 3. The loading mass is a bolt-and-nut with 10g in weight loosely attached to the structure as illustrated in figure 3.

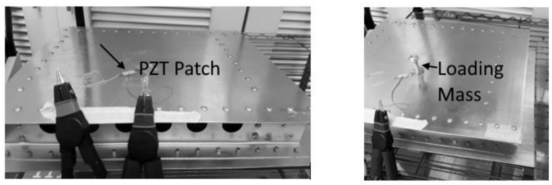

Figure 3 Aluminum Structure without the loading mass/with the loading mass

A piezoelectric patch (PZT sensor) is attached to the structure for monitoring the structural integrity. A professional impedance analyzer WK3260B is used to getting the impedance of the PZT patch over a typical frequency range (100kHz ~ 500kHz). The measured data is acquired with a data logging software. In the experiment, more than two hundred sets of data were collected with two loading conditions, they are labelled with Loading (with Loading mass) and No-Loading (without the loading mass).

The collected data are evaluated with a selected data as the baseline. The RMSD values are calculated over the whole frequency spectrum. However, it is reported that the effective frequency range for RMSD evaluation of a given structure is usually determined by a trial and error approach [4]. With reviewing the calculated RMSD, it is found a variation in the RMSD value for different measurements under the same loading condition as illustrated in figure 4, the variation may be contributed by instrumentation condition or environmental condition, such as temperature change.

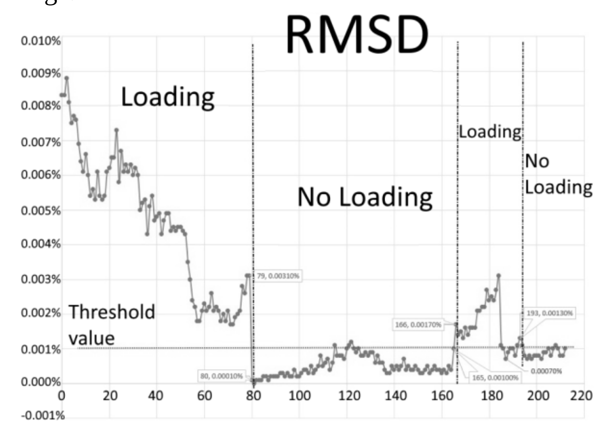

Figure 4 RMSD result for different loading conditions

As illustrated in the figure 4, it is difficult for users to set the threshold value for identifying the structural conditions (No-loading/Loading) based on the RMSD value as some overlapping area of the RMSD value for both "Loading" and "No-loading" conditions.

IV. Condition Classification with Deep Learning

With considering the difficulties encountering with RMSD approach, the Deep Learning [8] technique is evaluated to apply in the condition classification of our damage detection experiment. Deep Learning is one of machine learning methods commonly used in image recognition tasks. The deep learning process is divided into two phases. The first phase is the Training Phase, a large dataset is collected with the corresponding labels. It is used to teach the Machine Learning process how to classify different groups of images. A machine learning algorithm is adopted for summarizing the dataset into a Training set. The Training set will be utilized in the Predication Phase by the Trained Classifier. The Deep learning technique uses multiple transformation steps to extract features from model automatically. It is an advantage to adopt the Deep learning technique in SHM applications as the prior knowledge of structural model is not required. Convolutional Neural Networks (CNNs) is one of Deep learning architectures that has proven successful for image analysis [9]. Different models implementing CNNs have been proposed [10] to improve the image classification performance. The major differences among the different models are the number of layers and the interconnection structures.

To apply the deep learning technique, the Condition classification was modelled as an image classification problem. One of the approach is to visualize a FRF as a line-chart type image as illustrated in figure 1. The shape of the line-chart can be characterized to represent the EMI response of the structure. However, the effectiveness for visualizing the FRF in this approach is questionable. To preserve the detail of the FRF, the required resolution should be more than 1000 x 1000 in pixels. This image size will make our model to be incompatible for most of popular CNNs models as illustrated in figure 5 such as AlexNet, GoogLeNet[10]. It also increases the computational complexity even if we create our own CNN model. Furthermore, most of space in the line-chart representing the FRF contains no information. Therefore, a more suitable visual representation of the FRF should be considered instead of the line-chart representation.

CNNs Models	LeNet-5	AlexNet	OverFeat	GoogLeNet	VGG-16
Image Size	28x28	227x227	231x231	224x224	224x224

Figure 5 Image size of some popular CNN models [10]

Therefore, a color bar semantic as illustrated in figure 6 is proposed in this paper to adopt the deep learning for FRF-based problem. Under the color bar semantic, the vertical axis represents the frequency range. To align color bar image with the requirement of typical CNNs models, the horizontal axis will be extended with same number of data points as the vertical axis with same color intensity. Furthermore, this color bar semantic can be further extended to combine both imaginary part and the real part in the horizontal axis, it can maximize the information regarding the conditions of a structure with the active signature concept [11].

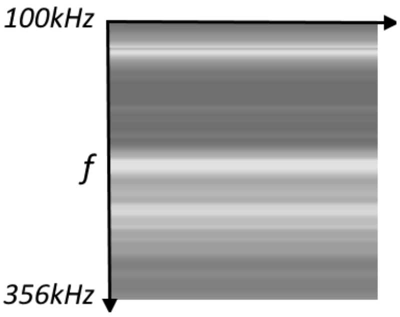

Figure 6 the FRF of the structure in Color bar

The value of the FRF will be encoded with the RGB color scheme with following equation

$$FRF(f) = R + G \times 256 + B \times 65536$$

where R, G, B are the color intensity for the Red, Green and Blue components of the RGB color scheme. For example, the impedance value 1500Ω will be represented by R=220, G=5 and B=0.

For the Deep Learning condition classification implementation, an interactive deep learning Training System, DIGITS [12] has been adopted. The DIGITS provides an intergraded environment for dataset preparation, the training network configuration and deployment, the training set creation.

For this experiment, 28 sets of data for the measurement with Loading Mass (Labelled with Loading) and 28 sets of data for the measurement without Loading Mass (Labelled with OK) were selected as the dataset as illustrated in figure 7. The rest of data is used as testing data for evaluating the resulting training set.

Label	Serial	RMSD	Condition	Remark
A16	1	0.3584%	Load	Training Data
A17	2	0.4481%	Load	Training Data
A18	3	0.4414%	Load	Training Data
A19	4	0.4305%	Load	Training Data
A20	5	0.4291%	Load	Training Data
A21	6	0.4232%	Load	Training Data
A22	7	0.4232%	Load	Training Data
A23	8	0.3962%	Load	Training Data
A24	9	0.3962%	Load	Training Data
A25	10	0.3880%	Load	Training Data
A26	11	0.3810%	Load	Training Data
A27	12	0.3870%	Load	Training Data

Figure 7 Selected dataset

Another important consideration for setting up the training model is the network selection and configuration. Two standard networks, AlexNet and GoogLeNet [10] are evaluated. The model based on the AlexNet did not converge to the reasonable accuracy within appropriate iterations (Epochs). As illustrated in figure 8, the final accuracy is around 50%.

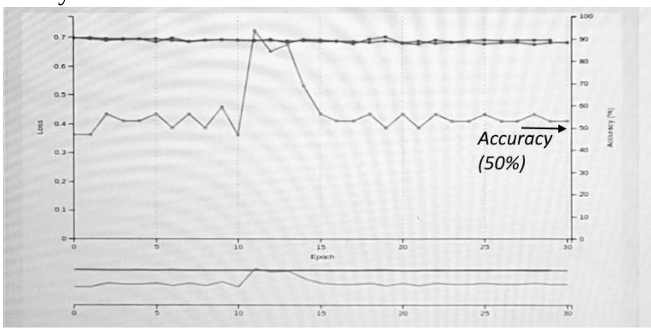

Figure 8 Training Curve with AlexNet based model

Moreover, the model based GoogLeNet demonstrated a very good performance in training stage with appropriate solver and parameters setting as shown in figure 9. The general difference among AlexNet and GoogLeNet is the number of layers, the number of layers for AlexNet and GoogLeNet are 8 layers and 22 layers respectively. The result demonstrated that increasing in the complexity of CNN network has a favorable effect for this experiment.

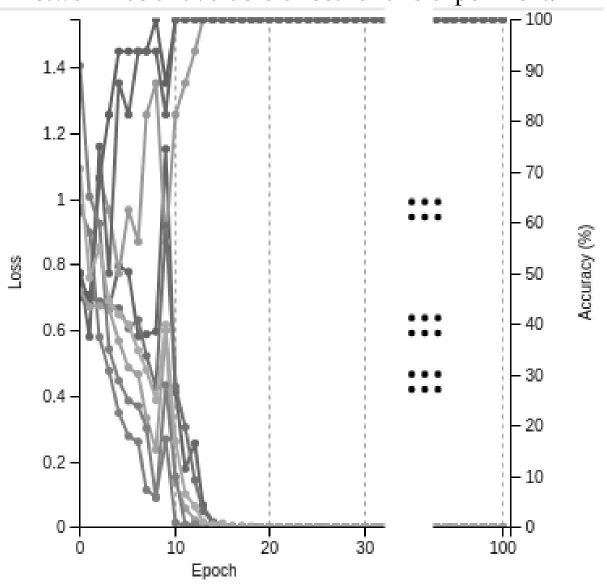

Figure 9 Training Curve with GoogLeNet based model

The created training set has been verified with the test data. The overall performance of the classification experiment is summarized in the figure 10.

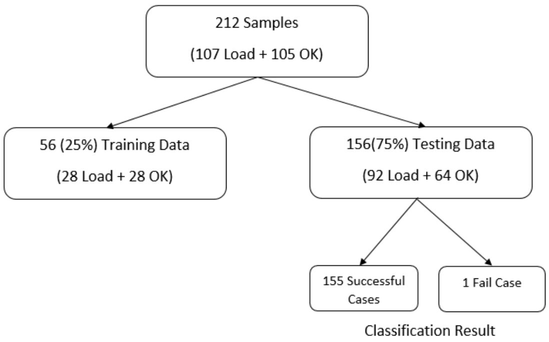

Figure 10 Classification performance with the developed Deep Learning Model

The result is very positive even for data with ambiguous RMSD value. For the 156 test data sets, only one error for data set #184 was observed as illustrated in figure 11. In fact, the error can be corrected by updating the training set with data set #184.

Label	Data#	RMSD	Data Label	prediction Result			
LOAD	176	0.00210%	/home/iavr/DLI/SHM2/TrainA/Test/data176-a.jpg	LOAD	91.43%	OK	8.57%
LOAD	177	0.00220%	/home/iavr/DLI/SHM2/TrainA/Test/data177-a.jpg	LOAD	91.43%	OK	8.57%
LOAD	178	0.00220%	/home/iavr/DLI/SHM2/TrainA/Test/data178-a.jpg	LOAD	74.86%	OK	25.14%
LOAD	179	0.00270%	/home/iavr/DLI/SHM2/TrainA/Test/data179-a.jpg	LOAD	90.96%	OK	9.04%
LOAD	180	0.00240%	/home/iavr/DLI/SHM2/TrainA/Test/data180-a.jpg	LOAD	90.96%	OK	9.04%
LOAD	181	0.00250%	/home/iavr/DLI/SHM2/TrainA/Test/data181-a.jpg	LOAD	95.77%	OK	4.23%
LOAD	182	0.00240%	/home/iavr/DLI/SHM2/TrainA/Test/data182-a.jpg	LOAD	95.77%	OK	4.23%
LOAD	183	0.00270%	/home/iavr/DLI/SHM2/TrainA/Test/data183-a.jpg	LOAD	95.63%	OK	4.37%
LOAD	184	0.00310%	/home/iavr/DLI/SHM2/TrainA/Test/data184-a.jpg	OK	100.00%	LOAD	0.00%
LOAD	185	0.00110%	/home/iavr/DLI/SHM2/TrainA/Test/data185-a.jpg	LOAD	98.68%	OK	1.32%
LOAD	186	0.00100%	/home/iavr/DLI/SHM2/TrainA/Test/data186-a.jpg	LOAD	95.82%	OK	4.18%
LOAD	187	0.00070%	/home/iavr/DLI/SHM2/TrainA/Test/data187-a.jpg	LOAD	95.82%	OK	4.18%
LOAD	188	0.00090%	/home/iavr/DLI/SHM2/TrainA/Test/data188-a.jpg	LOAD	99.29%	OK	0.71%

Figure 11 the selected predication result

V. Conclusion and Future Work

In this paper, the author proposed a novel framework for applying the deep learning method for the condition classification of the mechanical structure with the EMI technique. The deep learning approach outperformed the index-based RMSD approach in the robustness and sensitivity even with limited number of training data. The feature extraction and the classification process were embedded in the deep learning framework without the human participation.

Another contribution of this paper is to model a framework facilitating the use of deep learning method in any frequency domain SHM and condition monitoring problem. In the future, we will use the framework proposed for attempting the ambient variation problems of the EMI method with a systematic investigation. Furthermore, combining several signatures in one color bar image is another direction of investigation, such as active signature [11], multiple sensors response for identifying the location and severity.

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