Spectral Features-Based Damage Diagnosis of Structural Steel Plate

Pranesh Krishnan, Sazali Yaacob, Paulraj M P, Mohd Shukry Abdul Majid

Abstract*: Cracks and physical damages are a threat to the strength of the structures. Non-destructive test (NDT) measures are used to detect the damages at the earlier phase to avoid any major damages to the structures. Vibration signal processing is one of the NDT methods to determine the damages based on the experimental modal analysis. In this study, an experimental setup is devised to freely suspend a steel plate of size 30 cm by 60 cm. Based on the experimental modal analysis, the steel structure is struck using an impact hammer and the dispersed mechanical energy is bagged as vibration response using an accelerometer. The damages of size 512 µm to 1852 µm were manually simulated at arbitrary locations on the surface of the steel structure. The data acquisition procedure is repeated before and after the simulation of damage. The vibration signals are then processed, and the spectral features are extracted. The feature set is normalized between 0 and 1 are then mapped towards the condition of the plate to formulate the final dataset. Using a k-fold cross validation technique, the dataset is trained and tested using Least square support vector machine (LS-SVM) and k-nearest neighbor (KNN) classifiers. The results are compared and discussed.

Index Terms*: damage detection, experimental modal analysis, nondestructive testing, spectral features.

I. INTRODUCTION

Unidentified damages can put human safety at risk, cause long term machine downtimes, interruption in the production and subsequently increase the production cost. Early damage detection and possible location of the faults from the vibration measurements is one of the primary tasks of condition monitoring. Vibration based condition monitoring has been in practice since the late 1970s. Several approaches have been used in the literature which is categorized as: (a) Natural frequency based, (b) mode shape based, (c) mode shape curvature or strain mode shape based, (d) dynamic measured flexibility based, (e) matrix update based, (f) the non-linear method based, (g) neural network based and other methods. Carden and Fanning (Carden & Fanning, 2004) conducted a detailed review of the vibration based condition monitoring techniques. Their review emphasized on the structural engineering applications. They discussed various pattern recognition models. Yan et al. (Yan, Cheng, Wu, & Yam, 2007) summarized the state-of-the-art and development of vibration based structural damage detection methods. They discussed on the traditional type (frequency response function, change in natural frequency, change in structural stiffness) and modern type (neural network, wavelet analysis, genetic algorithm) vibration-based damage detection. Further, Fan and Qiao (Fan & Qiao, 2011) extended the review on the vibration based damage identification methods. They summarized the damage identification algorithms developed for beam type and plate type structures. They also highlighted the limitations of the existing damage detection methods. They finally addressed the need for the robust multiple damage detection methods, quantification methods for damage magnitude, and viable damage identification method. Zhou et al. (Zhou, Zkxw, Fq, Zkxw, & Fq, 2009) used a vibration exciter and Fibre Bragg Gratings (FBG) sensors to detect damage from a steel plate. They employed multiple scale entropy and support vector machine to detect the presence of the damage. Zhang et al. (Zhang, Jiao, Ding, Zhang, & Jiang, 2018) conducted a simulation study on the shear crack on steel plates. Rus et al. (Rus, Lee, Chang, & Wooh, 2006) developed an optimization technique for steel plate damage detection based on the noisy impact test. They designed an optimal filter to reduce the effect of noise. Gao et al. (Gao, Guo, & Zhao, 2014) conducted an experimental study to detect the multi-damage in steel plates based non-modal method. They presented a damage localization index (IFS flexibility). They also discussed on the effect of boundary condition and damage magnitude. Alavi et al. (Alavi, Hasni, Lajnef, & Chatti, 2016) presented a method for crack growth detection in steel plates. Damage growth was studied using data fusion of multiple sensors and damage progression was studied using individual sensors. Zima and Rucka (Zima & Rucka, 2015) investigated the damage detection using guided wave propagation technique. They used a continuous wavelet transform to find the reflected waves in the lamb wave signals. Several researchers have adopted the vibration-based damage diagnosis in the fields of rotating machinery, civil engineering, structural health monitoring,

In this work, the existence of damage is identified using the support vector machine (SVM) model developed using the spectral features extracted from the vibration response. Based on the experimental modal analysis, a protocol is designed to excite a freely suspended steel structure. The distribution of the vibration response is captured using the accelerometers.

Revised Manuscript Received on September 05, 2019.

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The excitation point and the placement of accelerometers are changed to record the data throughout the structure. Damages are simulated and the experiment is repeated in the damaged condition. The vibration signal is further trimmed and segmented into frames. The spectral features are further extracted from each frame to constitute the feature set. The feature vectors are normalized and the condition of the steel structure are labelled accordingly to form the final dataset. A support vector modal is constructed and trained based on the k fold cross validation method. The network model is tested and the classification accuracy is reported.

II. EXPERIMENTAL METHODS

For this study, a stainless-steel plate of 60 cm by 30 cm was considered. An experimental framework was designed to loosely support the steel plate. The selection of the steel structure, the dimensions, numbering format and the details of the procedure has been discussed in detail in the author's previous paper (Paulraj, Yaacob, Abdul Majid, Kazim, & Krishnan, 2013; Paulraj, Yaacob, Abdul Majid, & Krishnan, 2012).

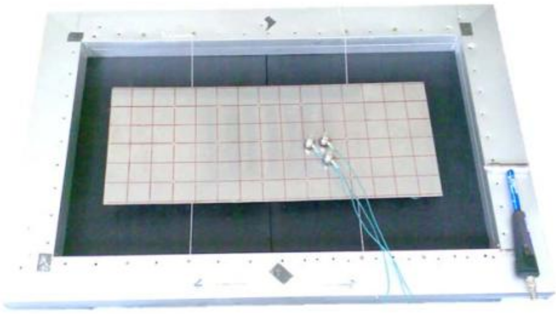

Figure 1. Experimental support for loosely supported steel plate.

A. Data collection

The cells are evenly divided and only 36 chambers at the center of the plate are considered for the experiment. The data collection protocol is designed by changing the locations of the impact points and accelerometers (a combination of roving hammer and roving accelerometer tests). The details of the data acquisition are detailed in the earlier publication by the author. The impact test is carried out for the 36 locations by changing the locations of the impact and the accelerometer which constitutes of 144 samples. Each sample contains 4 signals (1 impact hammer signals and 3 accelerometer signal). The dispersion of energy and the protocol is represented in Figures 1 until 4. The impact experiment is conducted on 10 similar steel plates under normal condition which forms 1440 normal samples.

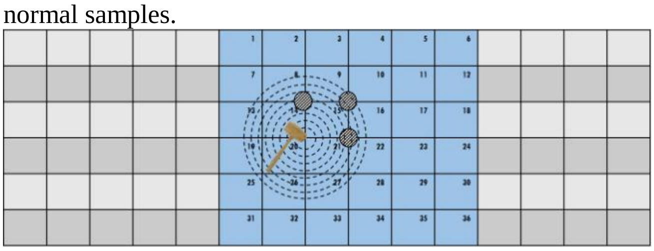

Figure 1. Accelerometer localization (protocol 1)

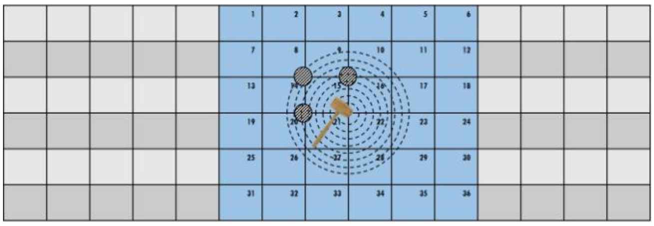

Figure 2. Accelerometer localization (protocol 2)

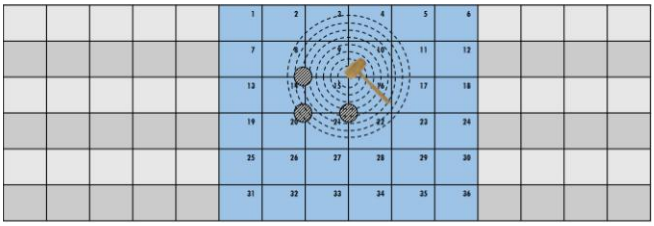

Figure 3. Accelerometer localization (protocol 3)

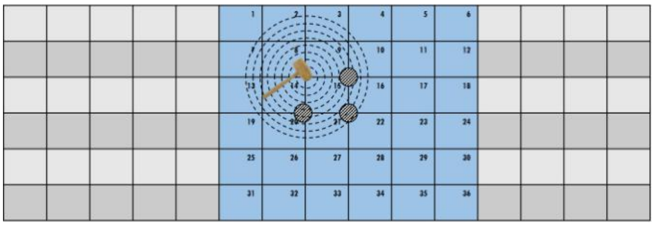

Figure 4. Accelerometer localization (protocol 4)

B. Damage simulation

Damages were simulated using drill bits on the surface of the steel plate at arbitrary locations for all the 10 plates. The depth of the damage was measured using a surface electron microscope (SEM). The average depths of the simulated damages were 1182 µm. The experiment is repeated after the damage simulation for all the 144 locations in the 10 plates to form 1440 damaged samples.

III. FEATURE EXTRACTION

Features carry dominant characteristics of the signal by reducing the dimensionality without losing the information. The vibration signal represents an exponential decay of the energy dispersed through the structure after the impact with respect to time. The signal spans for 20 seconds, however, the time of strike of the impact hammer on the steel plate is inconsistent throughout the experiment. Also, the exponential decay is not consistent throughout all the locations of the structure. The raw signal is the signal is trimmed and is represented in Figure 5.

Fast Fourier Transform (FFT) is computed over the raw signal is represent the frequency components of the signal. Figure 6 shows the FFT plot of the complete signal.

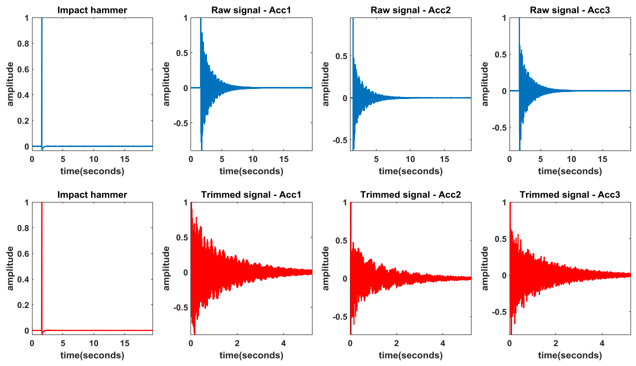

Figure 5. Raw and trimmed accelerometer signals

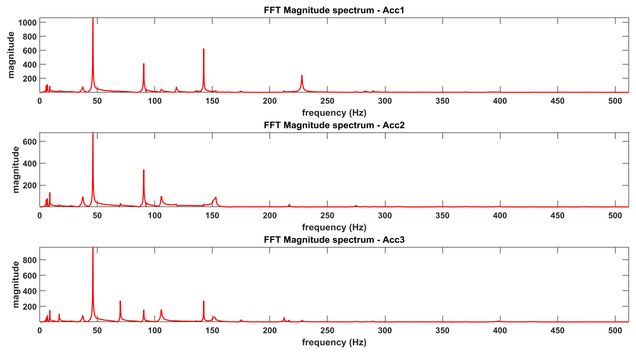

Figure 6. FFT magnitude spectrum of a typical signal

To effectively study the features, the vibration signal is segmented into frames of 1024 samples.

Spectral Centroid

The spectral centroid is widely used in speech research to identify the robust and dominant frequency. The spectral centroid for the vibration signal is calculated using Equation 1 as shown below.

$$SC = \frac{\int kX(k)dk}{\int X(k)dk} \quad (1)$$

where X(k) represents the FFT output and k represents the number of FFT components.

Spectral Centroid frequency

The spectral centroid frequency is computed as the average of amplitude weighted frequencies, divided by the total amplitude. The spectral centroid frequency for the vibration signal is computed based on Equation 2 as shown below

$$SCF_i = \frac{\sum_{n=1}^{M} f * S[f] w_i [f]}{\sum_{n=1}^{M} S[f] w_i [f]} \quad (2)$$

where M is the number of frequency bins.

IV. CLASSIFICATION

Data preprocessing is referred to the set of procedures used to process the raw data for further processing such as classification or clustering. The dataset derived from the features does not follow a uniform data distribution. Hence the feature set is rescaled between a certain range to enhance the performance of the classifier. The spectral features derived from the vibration signals are rescaled between ‘0’ and ‘1’ and associated with the class to form the dataset for classification.

Support vector machine (SVM) model is a machine learning algorithm based on the statistical learning. The SVM model is chosen in this study to classify the presence of damage. In this method, we plot each data as a point in the n-dimensional space with the value of each feature being the value of the particular coordinate. The classification is performed by finding the hyperplane that differentiates between the two classes. Hence finding the right hyperplane becomes very crucial in SVM. By maximizing the distance, also known as the margin between the nearest data point and the hyperplane will determine the right hyperplane. The kernel method is used to transform the low dimensional input space to a higher dimensional space in a non-linear separation problem. The ‘fitcsvm’ function in MATLAB is used to model the SVM. ‘Radial basis function’ kernel is used to classify between drowsy and alert classes.

K-Nearest neighbor algorithm (*k-NN*) is one of the simplest and easy to implement a supervised machine learning algorithm. The K factor is very crucial in determining the class boundaries. The boundaries become smooth with increased values of K. The training error rate and the validation error rate are the two parameters used to access for the values of K. The ‘**fitcknn**’ function in MATLAB is used to model the KNN classifier. The ‘**minkowski**’ method is used as a distance metric, and the number of neighbors value is chosen to be 3 in this classification method.

V. RESULTS

The spectral features namely spectral centroid, spectral centroid frequency is extracted for FFT plot of the vibration signal. Support vector machine is used to train the feature matrix. K-fold cross validation method is used to process the dataset into training and testing. The average classification accuracy, for the KNN and SVM classifiers are calculated and the results are tabulated in Table I.

Table II. Average classification accuracy

Classifiers	Average class accuracy	
	Dataset 1	**Dataset 2**
K-Nearest neighbor	**95.2**	**94.6**
Support vector Machine	93.10	92.50

VI. CONCLUSION

To conclude, the presence of damage is detected using the support vector machine (SVM) model developed using the spectral features extracted from the vibration response. Based on the experimental modal analysis, a protocol is designed to excite a freely suspended steel structure. The distribution of the vibration response is captured using the accelerometers. The excitation point and the placement of accelerometers are changed to record the data throughout the structure. Damages are simulated and the experiment is repeated in the damaged condition.

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further trimmed and segmented into frames. The spectral features are further extracted from each frame to constitute the feature set. The feature vectors are normalized and the condition of the steel structure are labelled accordingly to form the final dataset. A support vector modal is constructed and trained based on the k fold cross validation method. The network model is tested and the classification accuracy is reported.

ACKNOWLEDGMENT

The authors would like to thank the members of the Intelligent Automotive Systems research cluster and the post-graduate students of Universiti Kuala Lumpur and University Malaysia Perlis for their constructive and critical suggestions during the preparation of this manuscript.

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