Steel Plate Damage Diagnosis using Probabilistic Neural Network

Paulraj M P   Sazali Yaacob   M S Abdul Majid   Pranesh Krishnan
School of Mechatronic Engineering, Universiti Malaysia Perlis, Perlis, Malaysia.

Abstract - This paper discusses the application of frame energy based DFT spectral band features for the detection of damages in steel plates. A simple experimental model is devised to suspend the steel plates in a free-free condition. Experimental modal analysis methods are analyzed and protocols are formed to capture vibration signals from the steel plate using accelerometers when subjected to external impulse. Algorithms based on frame energy based DFT spectral band feature extraction are developed and prominent features are extracted. A Probabilistic Neural Network is modeled to classify the condition of the steel plate. The output of the network model is validated using Falhman testing criterion and the results are compared.

Keywords- Experimental Modal Analysis, Frame energy, Discrete Cosine Transformation, DFT spectral band, Falhman criterion, Structural Health Monitoring. Probabilistic Neural network.

I. INTRODUCTION

Damage can be defined as the changes introduced into a system that brings adverse effects in the present and future performance. Damage becomes expressive when it is compared between two different states of the system. Cracks are well-defined as any unintentional discontinuities in the shaft material. The occurrence of the faults or damages in the structures is quite unavoidable mainly due to environmental conditions, improper handling, poor maintenance and wear and tear. A detailed comprehensive survey on the nondestructive measuring techniques has been dealt by Brinksmeier [1]. Dimarogonas [2] presented a detailed review on nondestructive testing to detect and monitor cracks in beams, plates, rotors, and turbine plates. An extensive literature review of the state of art vibration analysis and damage detection has been published by S.W. Doebling [3]. A detailed survey of the state of art in the damage detection field using modal analysis has been presented by Richardson [4]. A detailed review of the different vibration and acoustic methods such as the time and frequency domains, acoustic emission techniques are presented by Tandon and Nakra [5]. Using fracture mechanics method, Dimarogonas [2] and Anifactis [6] computed the equivalent stiffness and developed a model for crack detection in beams. An experimental technique to estimate the location and depth of a crack in a beam has been developed by Adams and Cawley [7]. The methodology of crack detection based on natural frequency changes has been closely studied by Shen and Pierre [8].

The nondestructive approach is engaged towards the identification of the damages in the steel plate. Non Destructive Testing (NDT) can be defined as the study of the impulse response of a system due to an external excitation that confronts the dynamic nature of the system under test. The vibration signal is recorded from the system when it is subjected to an external excitation. The presence of damage in the system is studied by closely studying the vibration pattern at an instance. The vibration pattern carries the dynamic characteristics of the system such as fundamental frequency, damping ratio and mode shape.

In this paper, the vibration signal emanated from the steel plates excited by impulse signals are captured and analyzed. The dominant features from the vibration signals are extracted and a neural classifier is modeled to classify the condition of the steel plate.

II. METHODS AND MATERIALS

Experimental Modal Analysis (EMA) is defined as a process of acquiring acceleration response data (excitation of the structure using external force and obtaining the response to the force) and identification of the modal parameters [9]. A cold rolled steel plate of size 90cm length and 60cm width and of thickness 2mm and mass 1.2 kg is considered for this study.

An experimental structure to hold the stainless steel plate is fabricated where one side of the plate is hinged at the longer ends and the other end is set free. A swing frame structure is constructed using hollow iron pipes of width 3 feet and height 5 feet. The steel plate is hung (fixed-free condition) in equilibrium state using two adjustable hinges. The hinges are placed 30 cm apart from each other to balance the weight of the steel plate and to avoid over damping during the experiment. The hinges are screwed intact to avoid absorption of the vibration signals when the steel plate is under excitation mode. The swing frame arrangement is positioned on the floor, so that it is free from external vibration sources. The Fixed Free swing frame arrangement is depicted in Figure 1.

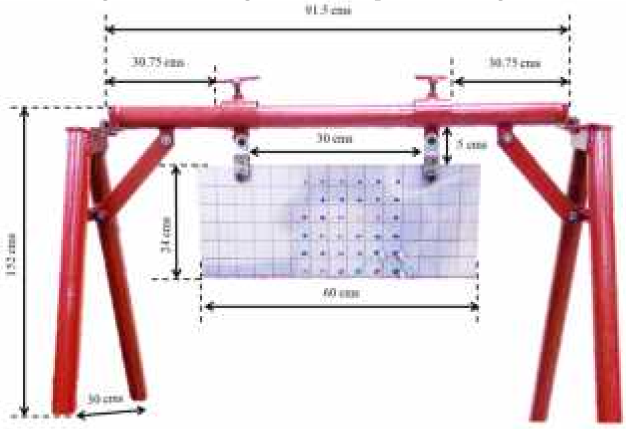

Figure 1: Fixed (Hinged) free steel plate

Using EMA, the vibration study can be performed in x, y and z planes Since the steel plate is an isotope, the characteristics of the vibration response in all three planes is similar, Hence the experimental design is developed to study the vibration response of the steel plate in x-y plane.

A. Roving hammer test

In this roving hammer testing procedure, the structure under test is mounted on the experimental setup. The accelerometers locations are evenly distributed over the structure. An impulse signal is generated on the structure by striking the impact hammer at different locations and observing the vibration acceleration pattern at different locations. The location of strike of the impact hammer is randomly selected. The number of accelerometers used in this test depends on the dimensions of the structure and the location of interest. Figure 2 depicts the roving hammer test where the location of the impact hammer is changed during every test while the accelerometers are placed intact in the numbered locations

B. Roving accelerometer test

The roving accelerometer test is similar to the roving hammer test. In this test the structure under test is mounted on the experimental setup and the location of strike of the impact hammer is fixed. The accelerometers are placed at even locations on the structure. The location of excitation is fixed at the same place throughout the test, while the accelerometer locations are changed during every trial of the test. The accelerometer roving test is shown in Figure 3.

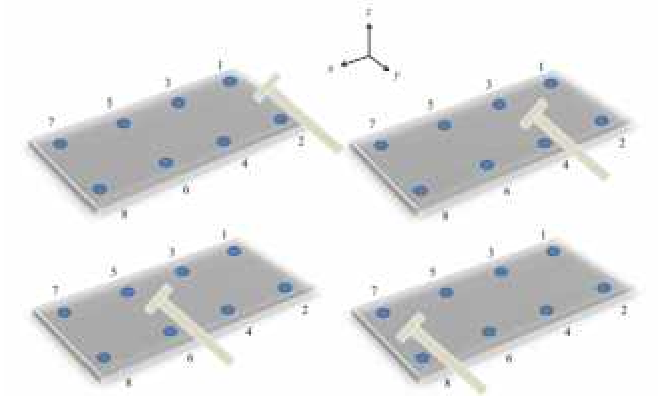

Figure 2: Roving hammer test

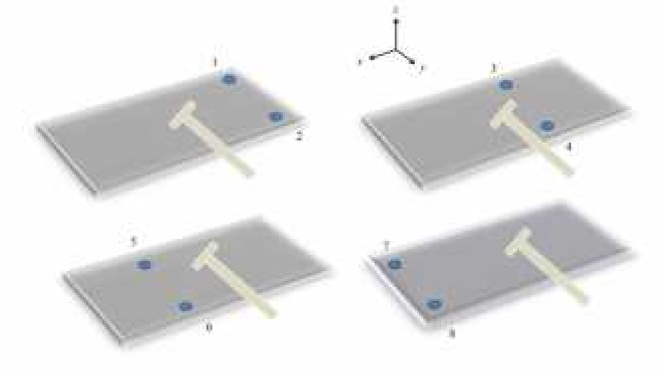

Figure 3: Roving accelerometer test

C. Materials and Protocol Design

The data collection protocol is the set of methods or rules framed to ensure the consistency of the measured vibration signals throughout the data collection process. The steel plate is divided into 6 rows and 15 columns. The area of the cell is 4 cm^2 and the cells are numbered sequentially from 1 to 36. An experimental protocol is designed based on both the roving hammer and roving accelerometer tests. The accelerometers are mounted over the corners of the cells based on the protocol design shown in Figure 4.

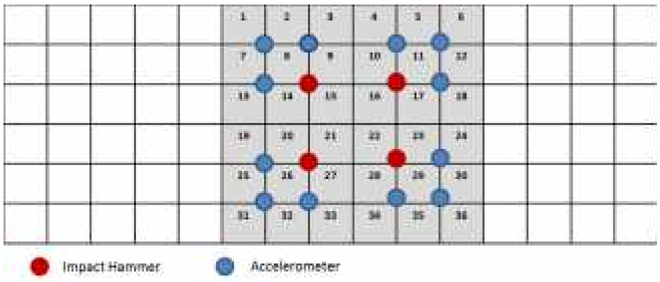

Figure 4: Experimental protocol design

An impulse is generated when the impact hammer strikes over the location on the steel plate. The accelerometers capture the vibration signal connected to the Data Acquisition System (DAQ). The experiment is carried out on all the 36 cells and 144 possible combinations of the 4 protocols by changing the positions of the accelerometers and the impact hammer. The recorded signals are sequentially numbered and saved.

Small micro damages of size 531 μm to 1870 μm are created throughout the steel plate inside the 36 cells and the data collection is carried out for all the locations. The experimental data is collected at various locations of the steel plate under normal and fault conditions. The experiment is repeated and the vibration signal is obtained from 10 steel plates of similar dimensions. Thus 1440 samples are captured and recorded for normal conditions. Similarly 1440 samples for fault conditions are collected after drilling small holes on the steel plates. The data collected is stored in the native 'XLF' file format supported by the DAQ. The files are later converted into 'WAV' file format for further processing through MATLAB.

III. FEATURE EXTRACTION

The vibration signals are captured using an experimental protocol from the steel plate at a sampling rate of 4 kHz [10]. The vibration signal is recorded for 20 seconds during the impact test. The time 't_p' corresponding to the first peak magnitude 'v_p' is identified and the signal recorded from (t_p – 0.5) seconds to (t_p + 14.5) seconds is trimmed for 15 seconds to maintain uniformity throughout the analysis. The trimmed signal is then segmented into definitive frames of size 1024. The representation of the blocked frames is shown in Figure 5.

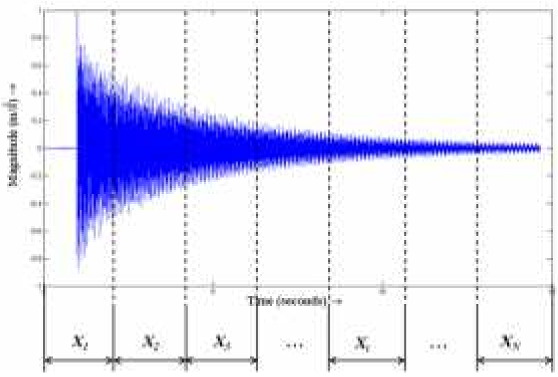

Figure 5. Vibration signal blocked into frames

A. Frame Energy

The total energy of a signal is defined as the sum of the squared magnitudes of the signal components. The law of conservation of energy states that, the energy can neither be created nor be destroyed, but can be transformed from one form to another. This law applies to this problem domain, where the energy in the form of mechanical force exerted by the impulse hammer is distributed all over the steel plate as vibration pattern. The energy in the form of vibration is affected by the damages present in the steel plate. The energy of the frame is calculated by computing the sum of the squared magnitudes of each frame. The Energy ***E*** of the signal is given by

$$\boldsymbol{E} = [e_1, e_2, e_3, \ldots, e_i, \ldots, e_N] \qquad (1)$$

where e_i is the frame energy in the i^{th} frame and it is represented as:

$$e_i = \sum_{j=1}^{1024} x_{ij}^2 \qquad (2)$$

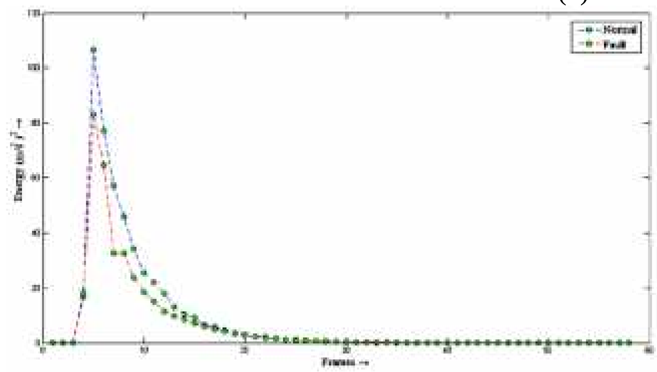

Figure 6: Typical Frame energy of normal and fault signals

A typical frame energy of a normal and faulty signa is shown in Figure 6.

B. DFT Spectral band feature extraction

The vibration signals recorded during the experiment poses time domain information. The signal is transformed from time domain into frequency domain using Fourier transformation. DFT transforms the time domain signal into frequency domain. Applying Fast Fourier transformation to the vibration signal, the DFT coefficients are observed. The absolute value of the DFT coefficients are computed and plotted. The frequency spectral response gives the frequency information of the vibration signals. The absolute DFT coefficients are represented in Equation (3). By observing the occurrence of the peak values in the frequency spectrum plot, the spectral bands for the fixed free condition are obtained and are tabulated in Table 1.

$$\boldsymbol{R} = \left[r_1, r_2, r_3, \ldots, r_i, \ldots, r_z\right] \qquad (3)$$

where r_i = i^{th} absolute DFT spectral coefficient.

The DFT spectrum of the vibration signals in both normal and fault conditions are depicted in Figures 7.

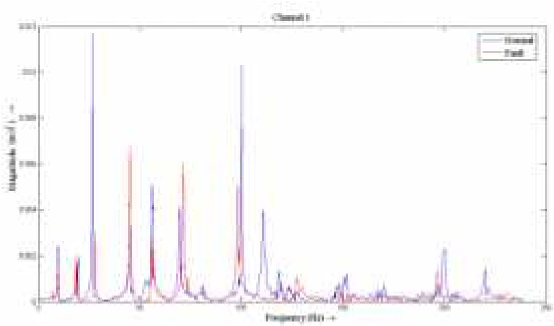

Figure 7:Frequency spectrum

TABLE I. FREQUENCY SPECTRAL BANDS

Band No	Frequency Range	Band No	Frequency Range
Band 1	6 Hz – 11 Hz	Band 10	114 Hz – 127 Hz
Band 2	15 Hz – 19 Hz	Band 11	130 Hz – 144 Hz
Band 3	22 Hz – 28 Hz	Band 12	144 Hz – 152 Hz
Band 4	35 Hz – 49 Hz	Band 13	153 Hz – 166 Hz
Band 5	52 Hz – 58 Hz	Band 14	166 Hz – 176 Hz
Band 6	65 Hz – 75 Hz	Band 15	180 Hz – 202 Hz
Band 7	75 Hz – 81 Hz	Band 16	204 Hz – 223 Hz
Band 8	88 Hz – 101 Hz	Band 17	228 Hz – 238 Hz
Band 9	101 Hz – 114 Hz	Band 18	238 Hz – 250 Hz

The DFT is calculated for the vibration signal using FFT method and the absolute values in the frequency spectrum are plotted. The spectrum is visually inspected for the peak spectral band frequencies and the spectral bands are formulated. The possible common occurrences of the spectral bands per each vibration channel are identified. 18 spectral bands for both normal and fault conditions are identified and tabulated in Table I. The sum of the squares of the defined spectral band coefficients are computed and used as features. The obtained spectral band features from all the three channels and combined to form a feature sample. The procedure is repeated for all the 1440 normal vibration signals and 1440 fault vibration signals to form the final feature matrix of size 2880 x 54 in fixed free method.

In the experimental method 54 features are extracted from 1440 normal samples and 1440 fault samples. The feature vectors are then associated with the condition (normal or fault) of the steel plate.

IV. CLASSIFICATION

Artificial Neural Networks are widely used for pattern classification. In this research work, a Probabilistic Neural Network Classifier [11] is modeled to classify the condition of the steel plate. The features extracted from the vibration signal are provided as input and the condition of the steel plate as output to the neural network.

The features extracted from three accelerometer channels constitute a feature sample. The features are extracted from the steel plates in both the normal and fault conditions. The database consists of 2880 samples (1440 normal and 1440 fault samples).

The extracted features are further processed to remove outliers. The features are labeled and then associated with condition of the steel plate. The dataset is normalized and the principal components are identified and the data dimensionality is reduced.

In the original dataset, the columns 1,2,3,4 contain the DCT moment information of Accelerometer 1, columns 5,6,7,8 contain the DCT moments of Accelerometer 2 and columns 9,10,11,12 contain the DCT moments of the Accelerometer 3.

A. Training: The Probabilistic Neural Network (PNN) is a variant of Radial basis function network. The processed features contain the input – output association. The network model contains three layers namely input, hidden and output. The input layer is provided with the feature vectors which constitutes the input neurons to the network. The output layer is associated with the target vectors corresponding to the input vectors. The spread factor and the goal are chosen. The maximum number of kernels is observed during the training. The 'newrbe' function available in MATLAB neural network toolbox is used to model, train and simulate the probabilistic neural network. The dataset is divided into training samples of 60%, 70% and 80% samples.

B. Testing: The trained network model is tested and validated against the 100% testing samples which include unseen inputs by the trained network. The network is tested with normal method and the 'threshold and margin criterion' proposed by Falhman [13].

V. RESULTS AND DISCUSSION

The training parameters of the PNN model are explained as shown in Table 2. The PNN model is trained and the results are validated in both normal method and Falhman method. The results of the trained network: mean classification accuracy, mean sensitivity, mean specificity and kernels are tabulated in Table 3.

TABLE 2: PNN Training Parameters

Input Neurons:	54
Spread:	0.5
Output Neurons:	1
Goal	0.01
Testing Tolerance:	0.1

TABLE 3: PNN Training Results

	Normal Testing			**Falhman Testing**		
	60%	**70%**	**80%**	**60%**	**70%**	**80%**
Mean Classification Accuracy	92.88	94.27	95.71	98.39	99.05	99.67
Mean Sensitivity	93.54	94.36	96.14	99.02	98.94	99.71
Mean Specificity	93.22	94.18	95.28	97.16	98.46	99.83
Kernels	835	875	934	835	875	934

The results show that 80 percent data samples produce better results compared to 60 percent and 70 percent samples. Though the larger the number of samples, the more the complexity and weighted connections of the network.

CONCLUSION

In this work, an experimental framework was developed based on the non-destructive testing and experimental modal analysis to hold the steel plate. A simple protocol based on the roving hammer and roving accelerometer tests were designed to perform impact testing and capture the vibration signal from the steel structure. Frame Energy based DFT spectral band features were extracted using algorithms from the vibration signals. Data preparation methods were developed to formulate the feature vectors for classifier models. Probabilistic Neural Network was modeled to classify the condition of the steel structure. The results of the network model were validated against the Falhman criterion and the results with the conventional network model were compared.

ACKNOWLEDGEMENT

The authors would like to thank Y.Bhg.Kol.Prof Dato' Dr. Khamarudin b. Hussin, Vice Chancellor, University Malaysia Perlis for his constant encouragement. This research is funded by E-Science (Grant No : **:** 03-01-15-SF0052) by the Ministry of Science and Technology (MOSTI), the Malaysian Government. The authors express their profound gratitude to Universiti Malaysia Perlis and the Ministry of Higher Studies, Malaysia. This study was conducted at University Malaysia Perlis

REFERENCES

[1]. Brinksmeier, E. (1989). State-of-the-art of nondestructive measurement of sub-surface material properties and damages, Precision Engineering, Vol 11, Issue 4, pp. 211-224, October 1989.

[2]. Dimarogonas, A,"Vibration Engineering", West Publishes, St.Paul, Minesota,1976.

[3]. S.W.Doebling, C.R. Farrar and M.B. Prime, "A summary review of vibration based damage identification methods", The Shock and Vibration Digest 30(2), pp 91-105, 1998.

[4]. Richardson MH, "Detection of damage in structures from changes in their dynamic (modal) properties – a survey", NUREG/CR-1931, U.S. Nuclear Regulatory Commission, Washington, District of Calumbia, 1980.

[5]. Tandon N, Nakra B C, "Vibration and acoustic monitoring technique for detection of defects in rolling element bearings a review", Shock and Vibration Digest, 24(3), pp 3-11, 1992.

[6]. Anifantis N, Rizos P, Dimarogonas A, "Identification of cracks by vibration analysis", American society of Mechanical Engineers, Design Division Publications DE 7., pp 189-197, 1985.

[7]. Cawley, P., & Adams, A. D.,"The location of defects in structures from measurements of natural frequencies", Journal of Strain Analysis", Vol 14, No 2. (1979) pp 49-57, 1979.

[8]. Shen, M.H, Pierre C, "Natural modes of Bernoulli Euler beams with symmetric cracks", Journal of Sound and Vibration 138, pp 115-134, 1990.

[9]. Ahlin, K., & Brandt, A.. "Experimental modal analysis in practice", Saven Edu Tech AB, Taby, Sweden, 2001.

[10]. Sophocles, J. O. (1996). Introduction to signal processing, Prentice Hall.

[11]. Specht. D.F., "Probabilistic Neural Networks", neural Networks., Vol 3., pp. 109-118, Pergamon Press, 1990.

[12]. Falhman, S. E., "An empirical study of learning speed in backpropagation Networks", CMU-CS-88-162, 1998.