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Damage Detection in Steel Plates using Discrete Cosine Transformation Techniques and Artificial Neural Network

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***Abstract*- In this paper, a simple method for crack identification in steel plates based on the Frame Energy based Discrete Cosine Transformation [DCT] moments is presented. A simple experimental procedure is also proposed to measure the vibration at different positions of the steel plate. The plate is excited by an impulse signal and made to vibrate. Frame Energy based DCT moment features are then extracted from the vibration signals which are measured at different locations. A simple neural network model is developed, trained by Back Propagation (BP), to associate the frame energy based DCT moment features with the damage or undamaged locations of the steel plate. The effectiveness of the system is validated through simulation.**

I. INTRODUCTION

Health monitoring of vibrating structure in machines is a important task in industries. 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 task of condition monitoring. Condition monitoring enables early detection of faults. In recent years there has been an increasing interest in the development of online condition monitoring systems due to the success in several applications.

A damage condition of a steel plate can be detected by the vibration signal propagating through it, when it is subjected to an impulse force. There are many technologies that have been developed to detect the faults in a gear box, bridge structures and bearings.

The existence of a crack in a steel plate reduces the stiffness of the plate and this reduction in stiffness ultimately reduces the natural frequencies. Further, this also changes the mode shape of vibration. An analysis of the propagation of the vibration signal makes it possible to detect the fault.

An extensive literature review of the state of art of vibration analysis and damage detection has been published by S.W. Doebling [1]. A detailed survey of the state of art in the damage detection field using modal analysis has been presented by Richardson [2]. 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 [3]. Using fracture mechanics method, Dimarogonas [4] and Anifactis [5] 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 [6]. The methodology of crack detection based on natural frequency changes has been closely studied by Shen and Pierre [7]. In this paper, it is proposed to detect the faulty location in a steel plate based on the energy based discrete cosine transformation features extracted from the vibration signal.

II. EXPERIMENTAL DESIGN AND DATA ACQUSITION

A. Data Acquisition System (DAQ)

Measurements of the vibration signals are acquired using a LMS SCADAS Mobile SCM01 Data Acquisition System. This system has 4 input channels and Ethernet connectivity. The features supported are : a maximum sampling frequency range of up to 102.4 kHz per channel, 105 dB signal to noise ratio and a high speed Ethernet connection. The DAQ system is monitored through the LMS Test Lab software which supports a wide range of applications.

B. Vibration and Pressure Transducers

Accelerometers are Vibration transducers which possess high natural frequencies compared to the vibration to be measured and indicate acceleration [8]. The piezoelectric accelerometers are widely preferred over the digital accelerometers in many applications due to its high accuracy and sensitivity. The general purpose Piezoelectric accelerometer with an input sensitivity of 10 / 31.6 / 100mV/g (g = 9.82 m/s2) and a resonant frequency of 28 kHz is used in this experimental work. Force transducers are used to produce impulse forces and commonly used for impact tests. The general purpose force transducers or so called impact hammer (Dytran 5800B2 -50LbF range, 100 mV/LbF) is used in this research work.

C. Experimental Setup

A simple experimental design to test the structure in a simply supported condition is proposed in this paper. An aluminum test rig of dimensions (90x60x3) cm is fabricated and used as a test bed. Two thin threads are tied across the test bench to hold the steel plate in a simply supported manner.

The distance between the two threads is 40 cm. An undamaged steel plate divided into 5 rows, 16 columns is considered for the experimental setup of dimensions (60x24x1) cm. The Steel plate is then mounted on the test rig as shown in Figure 1

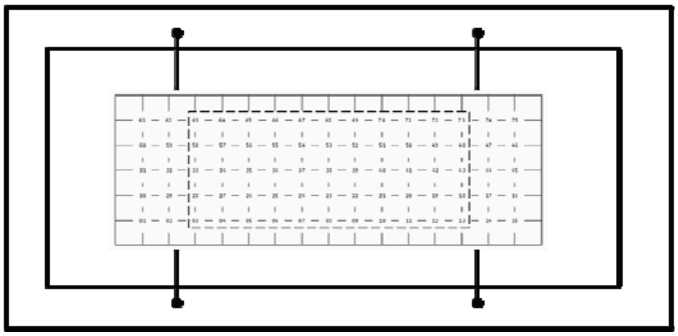


Fig. 1. Experimental Setup of Simply Supported Steel Plate

D. Estimation of Natural Frequency of Steel Plates

The natural frequency or eigen frequency of a system is the frequency at which the system oscillates. Any material possesses its own natural frequency. The natural frequency is a physical property which subsequently gets affected when there is a damage caused to the system. The sample steel plate has the following values: Poisson ratio (μ) = 0.3, Young's modulus (E) = 210N/mm2, Length (l) = 60x10-1m and Thickness (h) = 1x10-2m. The calculation for the natural frequency of the steel plate structure can be computed [9] using equation (2)

$$D = Eh^2 / 12(1-\mu^2) \text{ Nm} \qquad (1)$$

$$fn = (1/a^2) / \sqrt{D/\rho h} \text{ Hz} \qquad (2)$$

where D is the stiffness of the plate, (D = 1750Nm) and fn is the calculated natural frequency of the plate, (fn = 41.316 Hz)

E. Data Capturing Procedure

The plate is divided equally into 5 rows and 16 columns thus forming cells of size (4x4) cm2. The cell contact points (nodes) are numbered continuously. Based on the physical properties of the steel plate such as natural frequency (fn) and mode shape, the sampling frequency (fs) is set to 2048 Hz. The impact hammer is connected to the first ICP channel of the DAQ system. Three accelerometers are connected to the second, third and fourth ICP channels respectively. An impulse force is generated by hitting the impact hammer on a nodal point on the steel plate. The force of impact hammer hit is measured and recorded. The vibration propagated to the nearest three node points are measured using accelerometers. The placement of the accelerometers and the location of hit are shown in the Figure 2. The vibration signal is recorded for 15 seconds and the experiment is repeated for a minimum of 5 times. The above measurements are carried out in the steel plate without any damage. Damages of micro cracks are made externally through sharp nails inside the cells. The damages are made in 16 cells and the above experiment is repeated. Similarly the same procedure is repeated at all the nodal points and the vibration signals obtained at these nodal points are recorded. The signals captured are in the '.xdf' format, which.

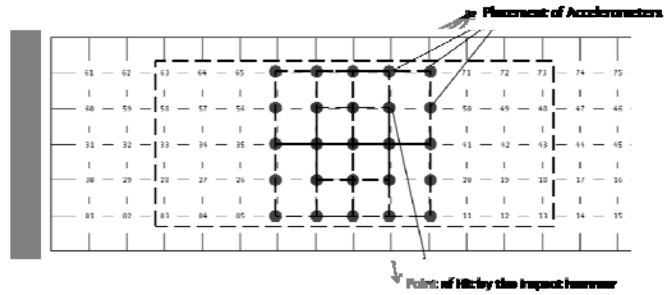


Fig. 2. Placement of Accelerometer and the Point of Hit

are then exported to '.wav' format using the LMS Text Lab software for analysis

III. FEATURE EXTRACTION

A. Signal Conditioning

The vibration signals at various locations are recorded at a sampling frequency of 2048 Hz. These signals are then segmented into windows such that each window frame has 256 samples. The discrete time domain representation of the vibration signal is written as.

$$x = \{x_1, x_2, x_i \ldots x_n\} \qquad (3)$$

where i = 1,2,3,…N and $x_1, x_2, x_i \ldots x_n$ are the window frames each having 256 samples. The high frequency components are removed using a hamming window w(n) where

$$w(n) = \alpha - (1-\alpha)\cos\left(2\pi N / N - 1\right) \qquad (4)$$

where $\alpha = 0.54$

B. Frame Energy

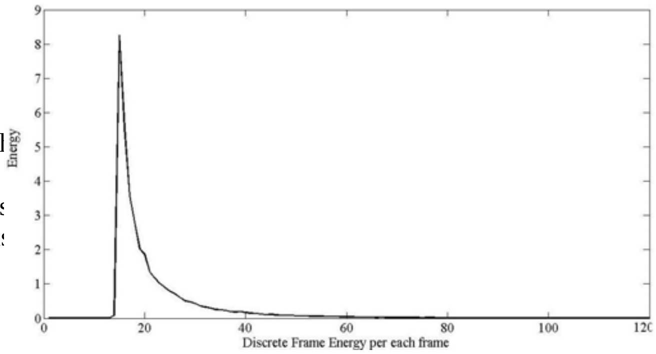
For each frame the total signal energy is computed and the variation in frame energy of a typical frame is shown in the Figure.3

C. Discrete Cosine Transformation Coefficients

The Discrete cosine transformation represents the signal as a sum of sinusoids of varying magnitudes and frequencies.

$$y(k) = w(k) \sum_{n=1}^{N} x(n) \cos\left(\pi(2n-1)(k-1)/2N\right) \qquad (5)$$

where $k = 1,2,3,\ldots N$



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whose absolute coefficient values greater than half the absolute maximum DCT coefficient value are considered for further analysis. It is observed that the first 64 DCT coefficients have their values greater than half the maximum absolute DCT coefficient value

D. Discrete Cosine Transformation Coefficients Moments

The Maximum amplitude values and their corresponding index values are calculated from the DCT Coefficients. The Moments for the first 10 DCT Coefficients are considered and shown in the figure 4

$$A = \{a_1, a_2, a_i, ..., a_n\} \tag{7}$$

where A is the maximum amplitude of the absolute Discrete Cosine Transformation Coefficient Moments.

$$B = \{b_1, b_2, b_i, ..., b_n\} \tag{8}$$

where B is the corresponding index values for the maximum DCT coefficients.

E. Rate of Change of the DCT Moments

The Rate of Change of the absolute Discrete Transform Coefficient Moments are calculated using the following equation

$$C = \left\{ \left(\frac{a_1 - a_2}{b_2 - b_1} \right), \left(\frac{a_2 - a_3}{b_3 - b_2} \right), \left(\frac{a_3 - a_4}{b_4 - b_3} \right), ..., \left(\frac{a_{n-1} - a_n}{b_n - b_{n-1}} \right) \right\} \tag{9}$$

F. Sum of Squares of the DCT Coefficients Moments

The difference between the product of the Discrete Cosine Transformation coefficient moments are calculated using the following equation

$$D = \{(a_2 b_2 - a_1 b_1), (a_3 b_3 - a_2 b_2), ..., (a_n b_n - a_{n-1} b_{n-1})\} \tag{10}$$

G. Product of the DCT Coefficients Moments Index and the Values

The absolute Discrete Cosine Transformation Moments values and the corresponding index are multiplied to form the following equation

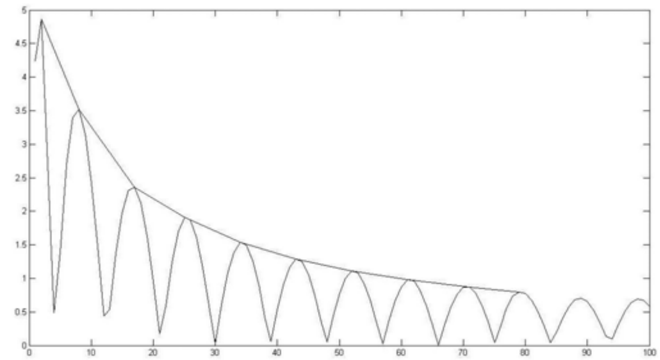

Fig. 4. Discrete Cosine Transform Coefficient Moments.

$$E = \{(a_1 b_1), (a_2 b_2), (a_3 b_3), ..., (a_n b_n)\} \tag{11}$$

H. Area of the DCT Coefficients Moments

The Area of the absolute DCT Coefficient Moments are calculated using the following equation

$$F = \left\{ (b_2 - b_1)\left(\frac{a_1 + a_2}{2} \right), (b_3 - b_2)\left(\frac{a_2 + a_3}{2} \right), ..., (b_{n-1} - b_n)\left(\frac{a_{n-1} + a_n}{2} \right) \right\}$$

I. Exponential Curve Fit for the DCT Coefficients Moments

The absolute DCT Coefficient Moments are fitted to an exponential curve using the following equation

$$F = \left(a.e^{-bx} + c.e^{-dx} \right) \tag{12}$$

The feature vectors derived from the above features for the feature matrix of which are then associated with the fault and normal conditions. The features derived from the frame energy based DCT moments are selected to form the feature set corresponding to an accelerometer signal. As the vibration is measured at three different locations simultaneously we have 52 frame energy based DCT moments and are associated to the condition of the steel plate

IV. CLASSIFICATION USING NEURAL NETWORK

A. Artificial Neural Network

An artificial neural network is an information processing system that has been developed as a generalization of the mathematical model for human cognition. [8]

Artificial Neural Networks (ANN) provides alternative form of computing that attempts to mimic the functionality of the brain. One of the most used learning methods in ANN is back propagation. The back propagation method (BP) is a learning procedure for multilayered feed forward neural networks.

BP is being used in a wide variety of application such as information processing, pattern recognition etc., BP procedure can be considered as a non linear regression technique which trains a neural network to acquire an input output association using limited number of samples chosen for a population of input output pattern. BP is most widely used learning algorithm since it is very simple to implement.

B. Neural Network Architecture

The neural network architecture consists of 4 layers, the first layer is the input layer, the second and the third layers are the hidden layers and the fourth layer is the output layer.

For training the neural network, 52 input neurons are used. The hidden layer has 7 neurons and the output layer has only one neuron. The output neuron is used to classify whether there is a fault present in the cell or not. Among the recorded 522 samples, 60 percent (313), 65 percent (339) and 70 percent (365) data samples are used for training and all the 522 data samples are used for testing the network model.

C. Neural Network Training and Results

A 3 layer neural network with 52 input neurons, 7 hidden neurons and 1 output neuron is considered. Each trial consists of 100 sets of randomized weight samples. The sum squared tolerance is fixed as 0.001. The input and hidden neurons are activated by the sigmoidal activation function. The network is trained by Levenberg Marquardt back propagation procedure. The trained neural network is tested with the test data containing 522 samples with a testing tolerance of 0.01. The convergence of the mean squared error is shown in Fig 5. The results for training the network is tabulated in Table 1 which shows the mean epoch and the mean classification rate.

TABLE I
NEURAL NETWORK TRAINING RESULTS

Input Neurons : 52 Output Neurons : 1 Hidden Layers : 1 Hidden Neurons : 7 Maximum Epoch : 100			Training Tolerance : 0.001 Testing Tolerance : 0.01 Testing Samples : 522 Activation Function : Sigmoidal			
	Training Samples					
	60 % = 313 samples		65 % = 339 samples		70 % = 365 samples	
No	Epochs	CR (%)	Epochs	CR (%)	Epochs	CR (%)
1	45	84.29	100	85.82	56	88.31
2	27	83.9	54	85.82	87	88.14
3	58	81.6	22	85.44	100	88.12
4	100	81.41	93	84.09	25	87.86
5	69	81.22	100	83.52	76	86.78
	59.5	82.48	73.8	84.93	68.8	87.84

V. CONCLUSION AND FUTURE WORK

This paper presents a simple testing method for the vibration based damage detection. Discrete cosine transformation is used in analyzing the vibration signals. A simple neural network is modeled and the faults are identified based on the discrete cosine transformation of frame energy features extracted from the captured vibration signal. The network model has a maximum and minimum classification accuracy of 88.14 and 86.78 respectively.

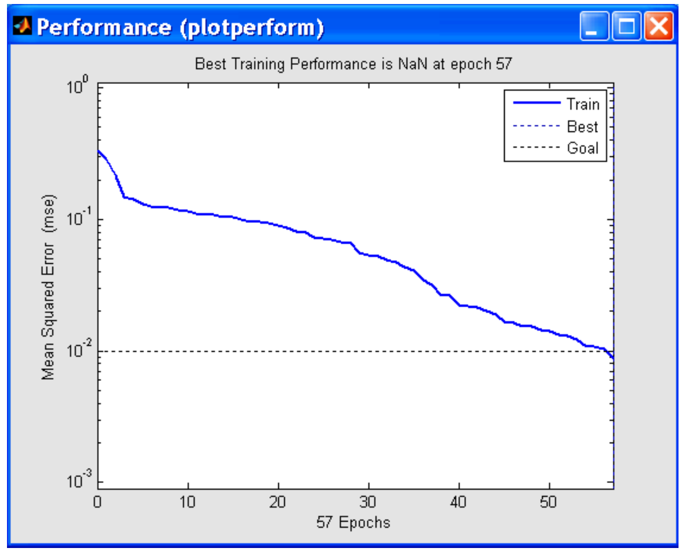

Fig 5. Convergence of the Mean Squared Error

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