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Comparison of Classifying the Material Mechanical Properties by using k-Nearest Neighbor and Neural Network Backpropagation

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Abstract – This paper present a development of a system with non-destructive testing on the material to define the mechanical properties of material. The experimental and testing of the material mechanical properties using vibration technique could determine the natural frequencies, the damping ratio and mode shapes of the structure. However, in this study, we only considering the natural frequencies and its amplitude of the material as the input data needed for training. As an extension for the study, the input data tested with various method of classifier. The *k*-Nearest Neighbor classifier and artificial neural network with Levenberg-Marquardt Backpropagation are developed to work as a system to classify the materials tested according to their mechanical properties. The result from the classification system shows that *k*-NN is giving the accuracy of 99.79783 % with the *k* value of 1 and in the other hand, Levenberg-Marquardt Backpropagation is giving the best classification rate of 99.86%.

1. Introduction

In mechanical properties study, the three common features that inspected and considered by researcher in mechanical properties study are the natural frequency, damping ratio and mode shape of the material. This is because most of the materials can be differentiate by using the above three aspects. In industry, a destructive test on material is practically and widely used to determine the material type and its mechanical properties to fulfilling the standard of the production. The non-destructive method is good as the material tested can be re-used and not wasted to the production. In this project, the material types that are considered are mild steel, stainless steel and aluminum with different thickness. The dimension of the plates is 40mm x 30mm. Theoretically, the plates would have the different mechanical properties because of the different thickness and type. As for boundary condition, we were using the free-free suspension of the plate. In practice, the almost free-free technique used is the elastic cord suspension. It is to avoid the difficulties on damping, environmental noise and flexibility of structure if the fixed boundary condition applied on the experiment. It is to avoid the difficulties on damping, environmental noise and flexibility of fixtures if the fixed boundary condition applied on the experiment.

2. Vibration Method and Analysis

2.1. Vibration

Vibration explained in terms of mechanical oscillations that may be periodic such as the motion and movement of a pendulum. The vibration testing is accomplished by applying external force onto the mechanical structure [7-8]. Impact hammer and shaker testing is the common method used in vibration testing.

2.2. Frequency Response Function (FRF)

In this study, the FRF signal is the component analyzed to get the natural frequencies value as the input data to the system. A frequency response function (FRF) is a transfer function, expressed in the frequency domain [7-8]. FRFs are the complex function with real and imaginary part of components. Fig. 2 and Fig. 3 show the example of the real components of the FRF signal. The FRF signal is defined as the ratio of output data from the accelerometer over input data from the impact hammer. The expression for the FRF signal used shows below in equation (1).

$$H(\omega) = \frac{X(\omega)}{F(\omega)} \tag{1}$$

2.3. Natural Frequencies

The natural frequencies of the materials used are the most important aspect considered in this study. Theoretically, the different material will have different natural frequencies based on its mechanical properties. The natural frequencies occur in the FRF signals from the experimental result used as the input to the system developed. The material tested is determined by the differences in the natural frequencies [7-8].

3. Experiment

The flowchart below presents the flow of the study. The Frequency Response Function (FRF) signals measured from the experiment. From the FRF signal, the natural frequencies and its amplitude can be determined. Afterward, the data validated using the reciprocity and modal analysis technique. The natural frequencies and distance from the impact and measured points are used as the features for the input of the system.

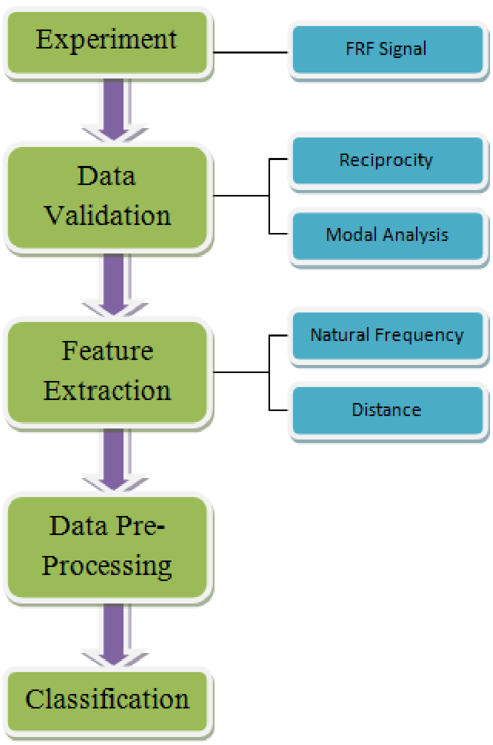

Figure 1. The flowchart of the study

From the experiment, natural frequencies gained referred in term of mode shape as shows in [3]. For example, first natural frequency referred as Mode 1. In this study, the first 3 modes and amplitudes in FRF signal are considered as the input to the system. Figure 2 show the basic experiment setup for the FRF measurement of the plate structure.

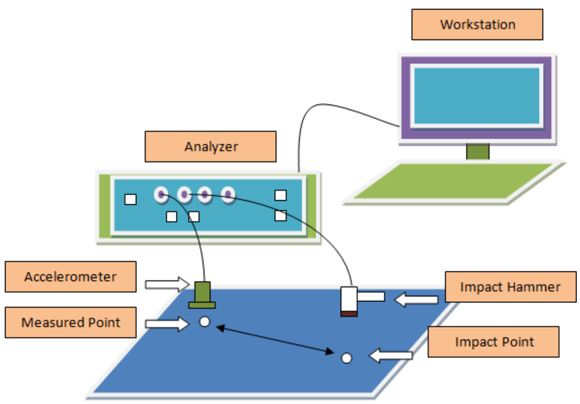

Figure 2. The impact and measured point on the plate structure

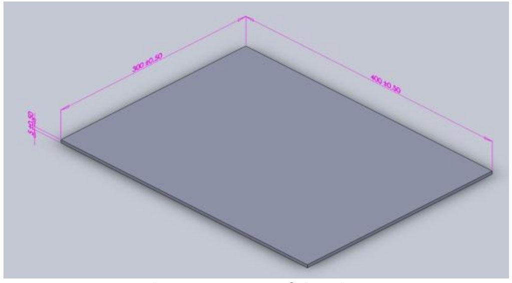

Figure 3. The CAD view of the plate structure

4. Data Validation of FRF Signal

The flowchart above presents the flow of the study. The Frequency Response Function (FRF) signals measured from the experiment. From the FRF signal, the natural frequencies and its amplitude can be determined. Afterward, the data validated using the reciprocity and modal analysis technique. The natural frequencies and distance from the impact and measured points are used as the features for the input of the system.

4.1. Reciprocity

The technique used to validate the data of the FRF signal is called reciprocity. The assumptions to this reciprocity technique is that the data measured at point 1 as excite at point 2 is same with the data measured at point 2 and excite at point 1.

$$\begin{array}{cc} & \text{inputs} \\ & \downarrow \\ \text{response} \longrightarrow & \begin{bmatrix} H_{11} & H_{12} & H_{13} & H_{14} \\ H_{21} & H_{22} & H_{23} & H_{24} \\ H_{31} & H_{32} & H_{33} & H_{34} \end{bmatrix} \end{array}$$

Figure 4. The matrix function of the reciprocity technique

Due to the reciprocity assumptions, it can be shown that the frequency response function between two points is basically the same whether you excite at point 1 and measure at point 2 or do it the otherwise. The expression as describe in equation (2).

$$H^{12} = H^{21} \tag{2}$$

4.2. Modal Analysis

Beside using the reciprocity technique, the other data validation technique that we used in this study is the modal analysis. Modal analysis is a process of studying, analyzing and describing the dynamic properties of any structure in the terms of natural frequencies, mode shapes and damping ratio [8]. Modal analysis always performed when measuring the vibration input that applied to the structure. In this study, modal analysis performed to validate the natural frequencies and its magnitude values.

The most stable peaks from the signal indicate the natural frequencies of the structure. Below shows the natural frequencies peak chosen as an input to the k-NN classifier. The peaks with the most ‘s’ is indicating the most suitable peak to be natural frequencies of the material.

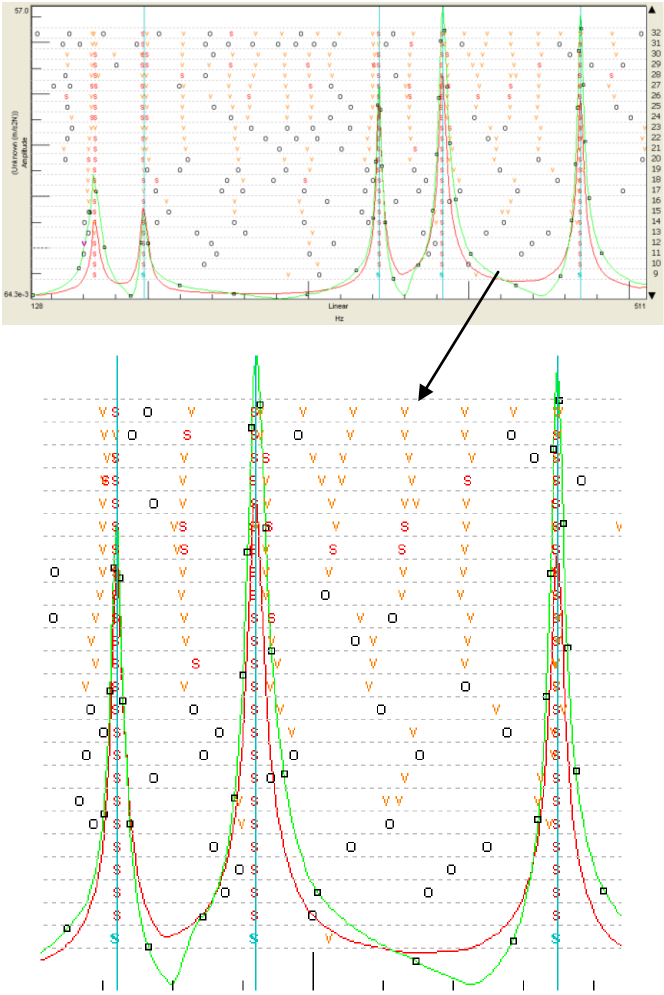

Figure 5. The modal analysis of the FRF signals

5. Classification

5.1. k-Nearest Neighbor

The *k*-Nearest Neighbor (k-NN) is the classifier used in this study. For the terms of pattern recognition, *k*-NN is a simple, instance based, lazy learning classification technique in classifying objects based on closest training examples in the feature space. The *k*-NN works by classifying the majority prediction of the nearest neighbor's category. This technique is suitable to compute the boundary. Since query instance will compare against all training signal, *k*-NN encounters high response time [9].

The Euclidean Distance used as the distance metric and described as in equation (3).

$$d_g(x,y) = \sum_{i=1}^{n} \sqrt{x_i^2 - y_i^2} \tag{3}$$

In this study, for each of the testing natural frequency and its amplitude, the minimum distance from the test FRF signals to each of the training data is calculated to locate the *k*-NN category of the training data sets.

As for the test run, the training data sets are located with k closest neighbors. From this testing, the system will indicate the class labels for each material types and properties.

5.2. Multi-Layer Perceptron Neural Network (MPLNN)

The MLPNN is the most common used technique of the neural network family. This method considered because of the ability to model from the simplest to the most complex functional relationship. This technique also proven applicable in various field of applications such as system identification, pattern recognition, signal processing, function approximation and control system. An MLPNN is capable of forming arbitrary decision boundaries and representing Boolean Function [6]. The most commonly adopted MLPNN is the backpropagation technique. The invention of the back-propagation learning algorithm for the MLP neural network is a landmark in the development history of neural networks. In fact, only after the introduction of this learning algorithm, have the powerful properties of neural networks been well recognized. The MLPNN need a set of data to be trained and tested through the algorithm. The set of data contains the inputs and outputs throughout the hidden layer. The input node element layer fed the hidden layer as the weight and

$$\Delta w_{kj} = \eta \delta_k O_j \tag{4}$$

Similar to the output and hidden layers, thus, the adaption of the weight between the hidden and input layer becomes:

$$\Delta w_{ji} = \eta \delta_j O_i \tag{5}$$

The backpropagation algorithm was created by generalizing the Widrow and Hoff learning rule to multiple layer networks and non-linear differentiable transfer functions [1]. Input vectors and the corresponding target or output vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by the user. Standard backpropagation is a gradient descent algorithm, as is the Widrow and Hoff learning rule, in which minimizing the sum squared error between the actual output and desired output. The mean squared error of the network is minimized through the algorithm by continually adjusting the weights and biases in the direction of the steepest descent with respect to the error [1-2].

This is known as gradient descent procedure. Networks with biases, at least one sigmoid neuron layer, and a linear output neuron layer are capable of approximating any function with a finite number of discontinuities. The best number of neurons and hidden layers to be selected in NN can be obtained by a simple trial and error or by optimization technique. Properly trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen.

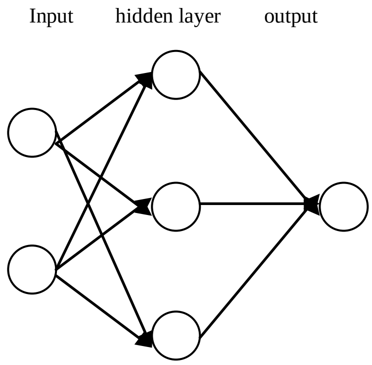

Figure 6. Multi layer perceptron neural network

The Levenberg-Marquardt Backpropagation is frequently used to solve the numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. This algorithm appears to be the fastest method for training moderate-sized feed forward neural networks (up to several hundred weights). It also has a very efficient MATLAB implementation, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB setting. These minimization problems arise especially in least squares curve fitting and programming [5]. The weights and biases of the neural network were set up randomly until we get the optimize result. The given data could be completely identified, which predicted that this method could be a supplementary tool to identify the differences in natural frequencies value of different plate used. The LMA is a very popular curve-fitting algorithm used in many software applications for solving generic curve-fitting problems [5].

6. Classification

The data of the natural frequencies implemented as the inputs to the system. The table below shows the number of training, classification accuracy, training time and number of epoch that has been taken as the result of the training and testing.

Table 1. The Natural Frequencies of Material

Natural Frequency	Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)
Mild Steel 5 mm	167	291	322
Mild Steel 6 mm	198	345	385
Stainless Steel 3mm	104	170	213

6.1. Result

All the tables below show the result for the training rate using the k-NN and Levenberg-Marquardt Backpropagation classifier. The result shows a slight difference in the average training rate for each classifier.

Table 2 and Table 3 below show the result of the classification rate using Levenberg-Marquardt Backpropagation.

Table 2. The Result of Neural Network Training (80%-20%)

Number of Training	Classification Accuracy	Training Time	Number of Epoch
1	100	1.6060	5
2	98.6	0.4719	3
3	100	0.4592	4
4	100	0.4169	3
5	100	0.4395	4
6	100	0.4919	6
7	100	0.4190	2
8	100	0.4184	3
9	100	0.4534	4
10	100	0.4054	2
Average	99.86		

Table 3. The Result of Neural Network Training (70%-30%)

Number of Training	Classification Accuracy	Training Time	Number of Epoch
1	100	1.8359	5
2	50	0.4249	1
3	100	0.4385	4
4	100	0.4264	3
5	100	0.4457	3
6	100	0.4447	3
7	100	0.4492	4
8	100	0.4534	4
9	100	0.4410	4
10	100	0.4505	4
Average	95		

Tables below show the result of the classification rate using *k*-NN classifier with the *k* value of 1, 2, 3, and 4.

Table 4. The Classification Result with *k*-NN Value of 1

k-Value	Classification Rate	Time Taken
1	100	0.1001
1	100	0.0927
1	98.00	0.0900
1	100	0.0865
1	100	0.0841
1	100	0.0828
1	99.97	0.0884
1	100	0.0873
1	100	0.0859
1	100	0.0823
Average	99.79	

Table 5. The Classification Result with *k*-NN Value of 2

k-Value	Classification Rate	Time Taken
2	97.77	0.1076
2	97.63	0.1015
2	97.77	0.1000
2	97.91	0.1082
2	97.36	0.1094
2	97.91	0.0974
2	96.80	0.0996
2	97.36	0.0972
2	97.77	0.1025
2	96.25	0.0981
Average	97.46	

Table 6. The Classification Result with *k*-NN Value of 3

k-Value	Classification Rate	Time Taken
3	95.13	0.1234
3	94.72	0.1038
3	96.52	0.1094
3	94.72	0.1104
3	95.41	0.1043
3	95.55	0.1039
3	95.55	0.1035
3	95.55	0.1070
3	94.16	0.1081
3	95.97	0.0982
Average	95.33	

Table 7. The Classification Result with *k*-NN Value of 4

k-Value	Classification Rate	Time Taken
4	91.11	0.1120
4	91.35	0.0933
4	91.23	0.1050
4	90.00	0.0964
4	92.34	0.0996
4	90.12	0.0961
4	91.35	0.1030
4	90.00	0.1024
4	90.37	0.0989
4	90.98	0.0993
Average	90.88	

6.2. Discussion

The purpose of this study is initially to develop a system to differentiate the mechanical properties of the material according to the natural frequencies value from FRF signal. As the natural frequency will be different depending on the different thickness and type of the material, we can easily classify the mechanical properties. The *k*-NN and artificial neural network methods used as the classifiers to classify the materials tested to their class as in training. The non-parametric identification method is proved to be the best method can be applied compared to the linear method. As for the training for *k*-NN, The experiment was tested repeatedly for each *k* values. After performing the *k*-NN classifier to the input, we manage to classify the natural frequency, the material types and also the mechanical properties of the material. From the table, it can be observed that the best classification rate is 99.79783% with the *k*-value of 1. The neural network method chosen is the Levenberg-Marquardt backpropagation technique. The non-parametric identification method is proved to be the best method can be applied compared to the linear method. After performing the neural network algorithm on the input, we manage to classify the natural frequency. From the table, it can be observed that the best classification rate is 99.86%.

7. Conclusion

The objective of the study is to investigate the effectiveness of the *k*-NN classifier and neural network in classifying the material and its properties. Data collected from the plates were analyzed by using the modal analysis method to get the natural frequencies for each. The natural frequencies for the plates used as the input data for the *k*-Nearest Neighbor and artificial neural network system. The system will determine the type of plate based on the natural frequencies value. The system will work neither with the different type of plate nor the different material mechanical properties. This is theoretically because the different natural frequencies also applied on the different type of material. After performing the *k*-Nearest Neighbor and neural network using the Levenberg-Marquardt Backpropagation, it shows that both algorithms can give a very good result in classifying the material using the mechanical properties provided as the input.

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