Iranian Society of Acoustics and Vibration
The 13th ISAV2023 International Conference on Acoustics and Vibration
20, 21 Dec 2023 Tehran - Iran

Crack Depth Specification of a Circular-Section Bar Using Peak Frequencies from Impact Test and Support Vector Machine Classification

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Abstract

Non-destructive data-driven approaches were noticed by researchers to crack identification of beam like structures. In this research, peak frequencies of the Fourier spectra of acceleration signals were used as crack depth classification features. Experimental data of impact tests are collected and first frequency peaks were extracted from circular bars with different crack depths. Extracted feature matrix was used to train an SVM model. The obtained performance of the classifier model shows that the frequency peaks can be used in the depth estimation of cracks, when the input force and consequently the FRFs are not available. While the sensor masses cause noticeable effects on the natural frequencies of the structure, peak frequencies of impact response of the sensor mounted systems still can indicate the depth of crack with acceptable accuracy. Also, the research showed that use of more number of peak frequencies can enhance the performance of classification. Acceptable performance of classification and cross-validation results were obtained using first 10 peak frequencies.

Keywords: Crack detection; Impact Test; Peak Frequency; SVM Classification.

1. Introduction

During the last few decades, intense research on the detection of cracks in structural or machine elements has been done. The nature of these studies is destructive or non-destructive, online or offline, model-based or data-driven. Among these approaches, non-destructive data-driven ones were developed by researchers to address this issue. Extracting vibration features and then machine learning techniques are used extensively in these approaches for crack depth detection of beam-like structures, having artificially-made cracks or notches. For example, in [1] experimentally measured natural frequencies using the Particle Swarm Optimization (PSO) method is used. This method considers the variation in local flexibility near the crack. In another study [2], the researchers used a novel method which utilizes the natural frequencies of the beam to measure and detect cracks. In another study [3] the size of a crack can be estimated by using changes in natural frequencies; however, significant damage may cause small changes in natural frequencies [4]. To detect cracks two approaches can be utilized. The first one is the use of crack models and to solve the inverse problem with a system identification approach. The second one is to use a non-parametric machine learning method such as artificial neural networks (ANNs) or support vector machine (SVM). An efficient numerical technique (ANN) is necessary to obtain significant results. The ANN technique does not need a previous model and is easy to use, but a sufficient training set of data is required [5]. One can also utilize Experimental Modal Analysis (EMA), which is based on using an impact of hammer test. EMA involves an extraction of natural frequencies through frequency response functions (FRF) at various surface cracks on the beam. Also, time domain identification with mathematically modelled cracks were reported in some researches [6].

In this paper, a practical methodology which uses peak frequencies from impact tests by hammer is utilized. Six steel bars for experimental tests were used: five bars with different crack depths and one intact bar without any cracks. This study will employ numerical fast Fourier transform (FFT) for picking several frequency peaks and Support Vector Machine Classification. First, we use the frequency peaks obtained from the impact test to train the SVM model. Second, we use the trained model to classify test data. The results show good performance of classification of the model train by only response data without the need of access to FRFs.

2. Impact test and peak frequencies

Experimental Modal Analysis (EMA) is an effective instrument for describing, understanding and modeling the dynamic behavior of a structure and also is the process of finding the inherent natural vibration of a structure. Therefore, if the natural vibration states are known, much of the vibration behavior of a structure can be predicted. A standard setup for experimental modal testing requires sensor technology, data acquisition and a computer for monitoring and analyzing the measurement data. The Frequency Response Function (FRF) of a system indicates the ratio of the Fourier transform of output signal divided by the Fourier transform of the input. If the output is acceleration signal and the input is the hammer force, the formula of the FRF in frequency domain is as follows:

$$FRF(\omega) = \frac{A(\omega)}{F(\omega)}. \tag{1}$$

So, the excitation spectrum $F(\omega)$ is required as well, and input force should be recorded. One can utilize (FRFs) and its variations due to crack for crack detection.

If excitation force is not measured, FRFs are no longer available and only the output acceleration spectra $A(\omega)$ can be used in the training process. In the present experiment, we lacked sensors for measuring input signals; therefore, frequency peaks the output acceleration spectra were used. Obviously, depending on the strength of the hammer impact, peak amplitudes in the spectrum vary, and they cannot be used as crack depth indicators in model training. So, only frequencies associated to the peaks are recorded as training features.

If the mass of sensors are comparable to the mass of structures, the extracted peak frequencies are not actually the natural frequencies of the structure due to the effects on structure inertia. This is the case in the study where the weights of the two sensors are relatively large compared to that of circular bars.

3. Support Vector Machine as a crack classifier

In the realm of machine learning, support vector machines (SVMs), also known as support vector networks, are supervised learning models accompanied by learning algorithms. These algorithms are designed to scrutinize data for the purposes of classification and regression analysis. SVMs find applications in a variety of real-world scenarios such as text and hypertext categorization, image classification, satellite data classification, handwritten character recognition, and applications in biological and other sciences.

SVM algorithms have found wide-ranging applications in fields like biology and other sciences. They are employed to classify proteins, achieving high accuracy rates, sometimes up to 90% correct classification.

In summary, support vector machines are versatile tools in machine learning, with applications in various scientific and engineering disciplines.

The core of the SVM algorithm is to find the best hyper-plane (direction) in the feature hyperspace which maximizes the margin between samples belonging to the two classes (Fig. 1). The samples located on the margin boundaries are called support vectors.

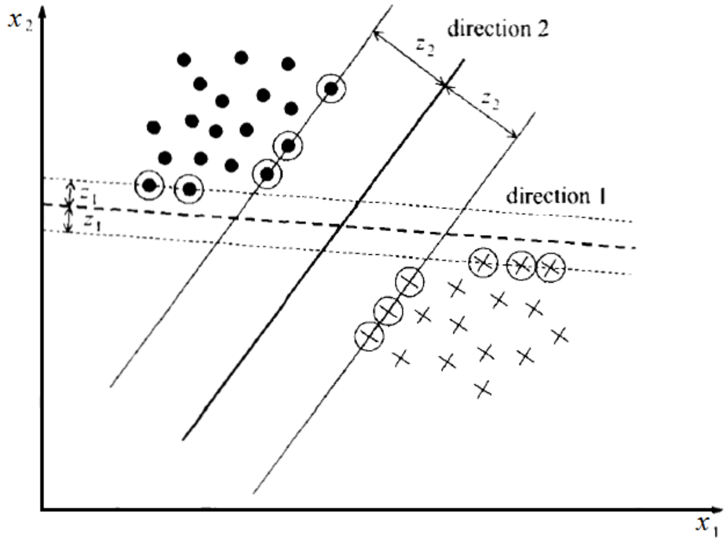

Figure 1. Optimizing the direction to maximize the class separating margin [7]

Kernel functions are applied in the SVM models in the cases that data should be transformed in a high-dimensional space to be separable.

Some fraction of data samples are used in model training process (finding the optimized hyper-plane) and then the remaining data can be used for classification test. Comparison of true and predicted test sample classes is performed via a confusion matrix and classification performance is measured. Finally, cross-validation algorithms can be implemented for model validation and checking the dependence of the model to changing the train and test subsets.

There are algorithms which extend two-class SVM models to multi-class ones. In the case of the present study a 6-class SVM model with RBF Kernels are trained to classify crack depths.

4. Case study

Six steel bars with the same length of 500 mm and a diameter of 20 mm were used in the current study. In the present experiments, an Electrical Discharge Machine (EDM) was used to create narrow notches considered as cracks in steel bars. EDM, also known as spark machining is a metal fabrication process whereby a desired shape is obtained by using electrical discharges (sparks). Material is removed from the work piece by a series of rapidly recurring current discharges between two electrodes, separated by a dielectric liquid and subject to an electric voltage. The first rod has no crack, while the other samples have cracks with depths of 2mm, to 10mm, mentioned in table 1. The cracks were created at a 150 mm distance from one side of the rod (Fig. 2).

Table 1. Crack depths of the specimens

Specimen Number	Crack Depth (mm)	Depth to Diameter Ratio (%)
1 (Intact bar)	0	0
2	2	10
3	4	20
4	6	30
5	8	40
6	10	50

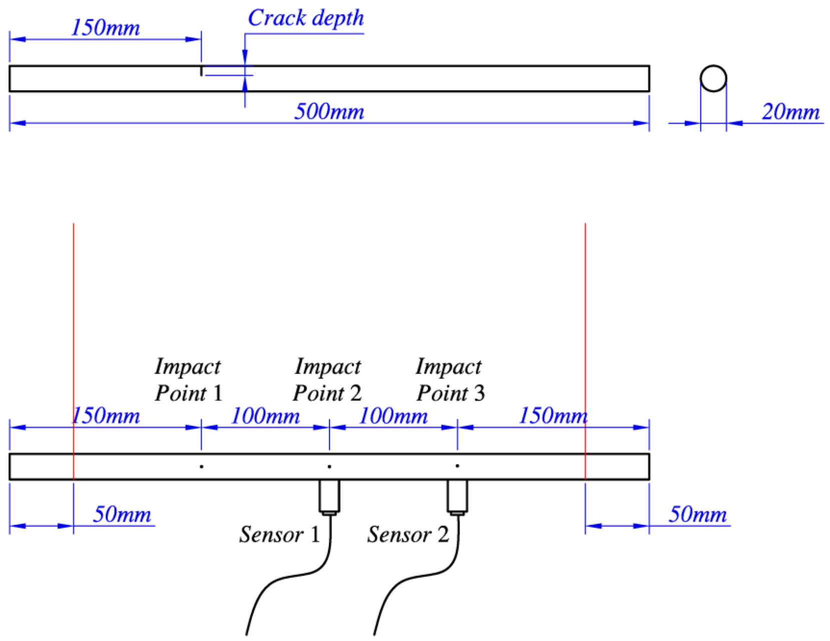

Figure 2.Geometry of the 6 bars, suspension points, sensor locations, and impact points

To perform the experiments, bar specimens need to be prepared.

- First, each rod will be suspended using two rubber bands, with one band placed 5cm from each end of the rod. Out of the total of six rods, five of them will have a crack artificially created along a 15cm section starting from one side of the rod.
- Next, the sensor 1 is placed at the middle point of the rod. The sensor 2 will be placed 10cm from the first sensor.
- Within three seconds, several impacts are made using the hammer at one of impact points.

Three different tests were performed:

Test A: In this test, the crack is located vertically downwards. The hammer impacts are applied vertically and from above to the selected areas.

Test B: In this test, the position of the crack is vertically downwards as in test A. But the hammer impacts are applied horizontally and inward to the selected areas.

Test C: In this test, the bars are rotated by 90 degrees and the crack position is bar side. The hammer impacts vertically and from above to the selected areas as in test A.

Schematic representation of the three tests is illustrated in the Fig. 3.

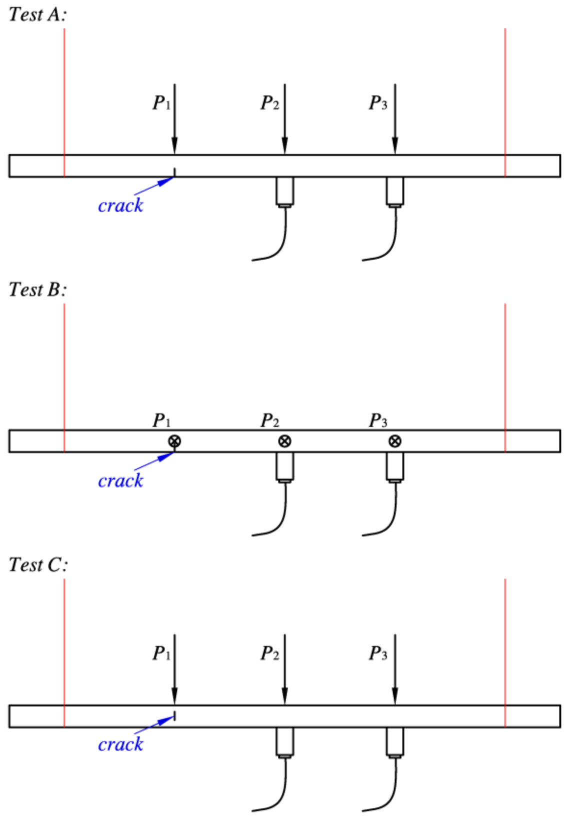

Figure 3. Illustrations of the three tests

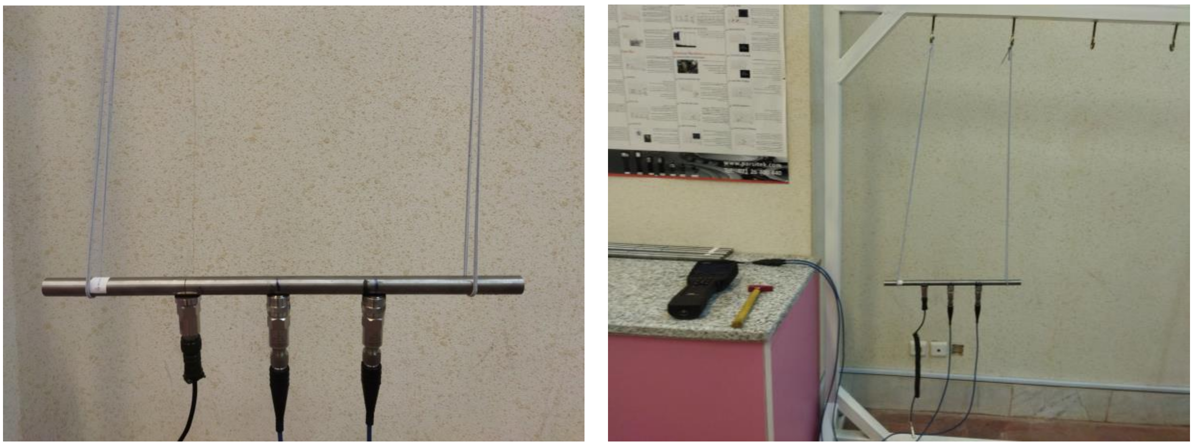

Figure 4. Sensors and data analyzer installation

According to the fig. 4, we have connected three sensors to each rod, and the left sensor does not record data and it is used only to maintain balance of the system. The two accelerometer sensors (CTC Accelerometer AC102, Top Exit 2 Pin Connector, 100 MV/G, ±10%, 30-900,000 CPM Frequency Response ±3dB) are connected to a portable vibration analyzer (SPM Leoneva Diamond). The time interval of data recording is set to 3 seconds and sampling frequency of the analyzer is set to 20,480Hz. In each recording several impacts are applied to one of impact points and the acceleration signals sensed by the two sensors are recorded.

5. Results

Through 3 tests, each at 3 impact points, for 6 specimens, and from 2 sensors, 108 time series signal records is created. Removing some repeated or damaged data, 100 time series were used in the analysis. One of time series records is indicated in the Fig. 5.

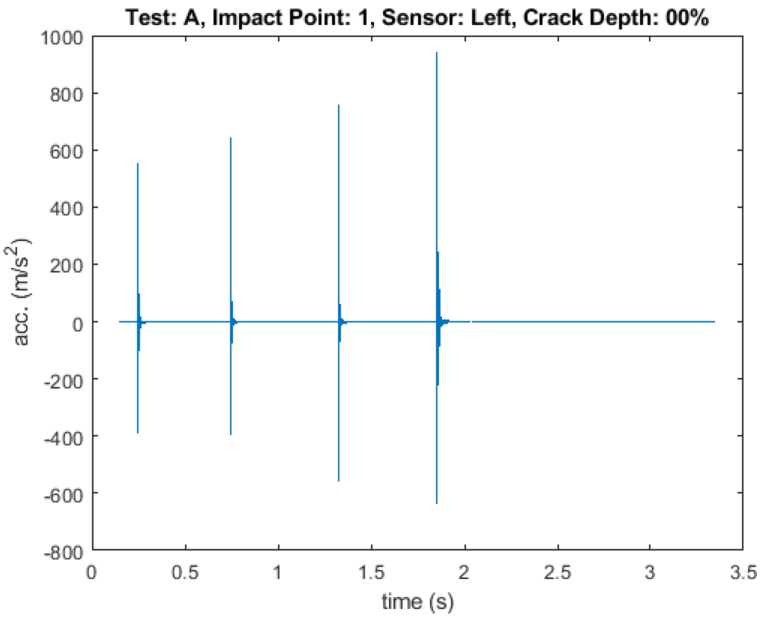

Figure 5. Signal recorded by the sensor 1 through 4 impacts at point 1 of the intact bar

The data of the Fourier transform test was taken and the frequency response spectrum of the two sensors was obtained. A finite element analysis of an intact bar showed that the natural frequencies are near: 370, 1000, 2000, 3300, … (Hz). So, the peaks only about these frequencies were picked. Fourier transformation was applied on the resultant signal from the impacts. The first 10 peaks were selected from the Fourier spectra. For instance, one of the Fourier spectra and several peaks are indicated in Fig. 6.

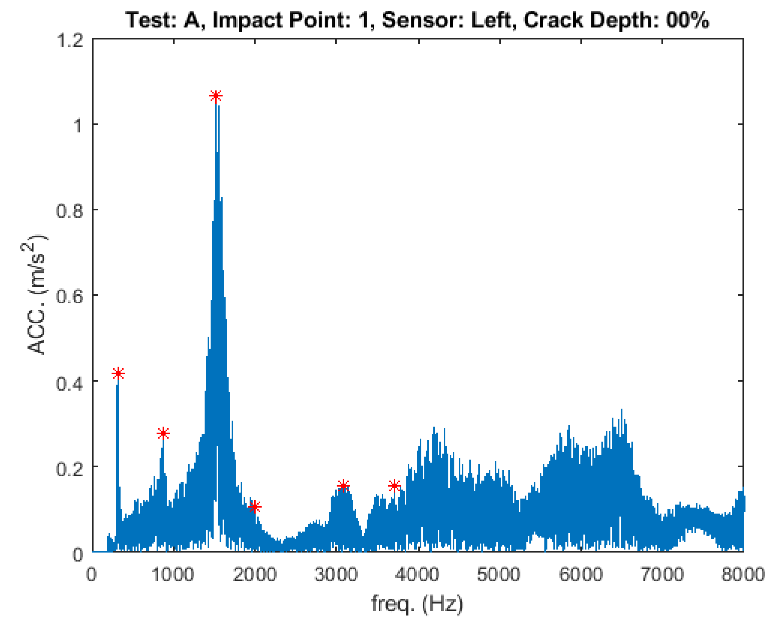

Figure 6. Fourier Spectrum and the first 6 peaks of the signal of Fig. 5

Fourier transform, peak frequency picking, and SVM classification of data is performed offline using MATLAB software. In the current study, the first 4 to 10 signal peaks were considered and fed into the machine learning algorithm to train the support vector machine model.

Number of 100 signal samples from three tests is obtained and recorded.75% of samples were used for training and 25% for testing. So, feature matrices of size 100 by 4 to 100 by 10 are used in different SVM modeling. Classification performances are listed in the table 2.

Table 2. Classification performances in different SVMs

Index of frequency peaks used	Model performance (%) (percent of correct classification)
1^{st}. to 4^{th}.	56
1^{st}. to 6^{th}.	68
1^{st}. to 8^{th}.	80
1^{st}. to 10^{th}.	88

The best performance was obtained when the first 10 frequency peaks were used as classification features and the results show 88 percent correct classification.

The result of confusion matrix which visualizes and summarizes the performance of a classification algorithm is shown in the Fig. 7.

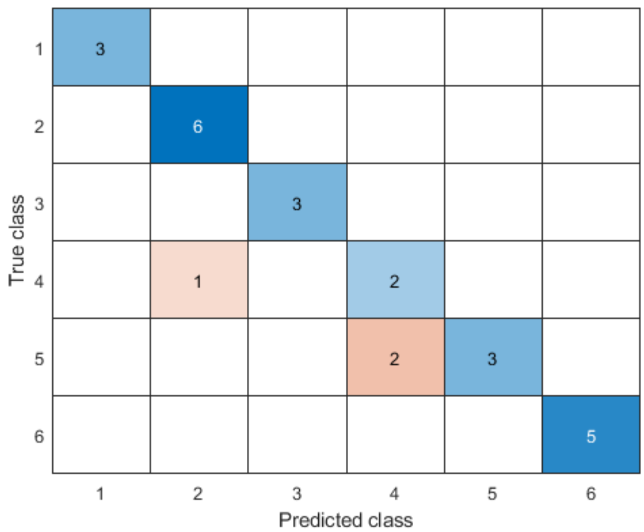

Figure 7. Confusion matrix for 100 by 10 feature matrix SVM classification

Also, the results of cross-validation with 5 folds show an average classification error of 0.17 with a standard deviation of 0.012.

6. Conclusion

Peak frequencies of the Fourier spectra of acceleration signals were used as crack depth classification features in this research. Experimental data of several impact tests are conducted and first frequency peaks were extracted from 6 circular bars with different crack depths.

Extracted feature matrix was used to train an SVM model. The obtained performance of the classifier model shows that the frequency peaks can be used in the depth estimation of cracks, when the input force and consequently the FRFs are not available.

Furthermore, while the sensor masses cause noticeable effects on the natural frequencies of the structure, peak frequencies of impact response of the sensor mounted systems still can indicate the depth of crack with acceptable accuracy.

Also, the research showed that use of more number of peak frequencies can increase the performance of classification.

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