Data-driven Fatigue Crack Evaluation based on Wave Propagation Data

Seongwoon Jeong
Civil and Environmental Engineering Department
Stanford University
Stanford, CA 94305-4020
swjeong3@stanford.edu

Abstract

This project presents a machine learning based fatigue crack sensor evaluation scheme without using a physical model. A supervised binary classification problem is defined to distinguish damaged steel specimens from intact specimens. Sets of time-series wave propagation data collected by the fatigue crack sensor are utilized for the proposed scheme. In order to apply supervised learning methods, different feature sets are defined based on the sensor data using Discrete Fourier Transform (DFT). Two-third of collected data are used as the training set while the rest are used as the test set. The preliminary analysis shows that the features consisting of amplitude distribution in frequency domain and the quadratic kernel function yield the most desirable performance. The trained SVM model, however, performs not very well for the test data set and needs to be improved, especially with larger data sets to reduce high variance. Nevertheless, the proposed learning scheme implies that the wave propagation data has some trend reflecting damage state of a specimen, which shows a great potential of machine learning techniques for fatigue crack analysis.

1 Introduction

As sensor technologies mature and become economically affordable, the use of sensors for the health monitoring of infrastructures, such as bridges, will continue to grow [1]. Developments of advanced sensing materials and devices, e.g. piezo lead zirconate titanate (PZT) and fiber Bragg grating (FBG) sensors, can also provide measurements for detailed and precise structural evaluation [2, 3]. Together with routine maintenance and inspection reports, the collected sensor data is expected to enable the diagnosis of potential structural problems and the prognosis for the need of structural strengthening and repairs. While current research trends of fatigue crack sensor mainly focus on the physical model based analysis to find cracks in infrastructure, little efforts have been spent on the machine learning based scheme, which has great potential with increasing amount of sensor data. The data analysis issues need to be dealt with to reduce the computational cost of the model based analysis as well as to find data patterns that has significant correlation with the level of damage.

In this project, a data-driven crack evaluation method based on the machine learning techniques is proposed to better support the decision making process of bridge owners. First of all, I defined a supervised binary classification problem to distinguish damaged and undamaged specimens. To develop and validate the proposed method, I prepared wave propagation data sets collected using a fatigue crack sensor developed by Lim et al [4], and divide the data into training set and test set. A few dog-bone steel specimens whose true damage status are already known are used for the wave propagation test [4]. The raw sensor data is pre-processed using Discrete Fourier Transform (DFT) so that different features that might represent the damage pattern can be extracted. Four different feature combinations are defined for preliminary training stage to find the most promising feature set for crack evaluation. In addition, different kernel functions for support vector machine (SVM) are implemented to reduce the training error. Lastly, the trained model is evaluated based on the test data set.

2 Related work

Research efforts on bridge monitoring and damage evaluation mostly focus on the traditional physical model based approaches, while little research efforts have started to attempt to implement machine learning method for the bridge management. Many studies on damage detection method proposed probabilistic model updating schemes based on finite element (FE) model of a structure [5, 6]. For example, Iman and Babak conducted probabilistic identification of a simulate damage on the Dowling Hall footbridge using Bayesian finite element (FE) model updating based on Markov chain sampling [6]. While this approach works well for the very significant damage of a simple bridge, but it is not appropriate to catch the onset of a damage and to evaluate complex structures involving very large degree of freedom followed by enormous computational cost.

To overcome such limitation and to detect the onset of damage, advanced sensing materials and sensors are developed and utilized [2, 3, 7]. A fatigue crack sensor proposed by Lim, for example, shows great performance to catch very tiny crack on a specimen based on the ultrasonic features collected by sensor [4]. However, this method requires many different combination of excitation to detect a small damage followed by long sensing duration.

On the other hands, some studies have started to implement machine learning methods for bridge management applications. O'Connor et al implemented Gaussian Process Regression (GPR) to find the environmental impacts on the behavior of Telegraph Road Bridge, MI, and suggested that there is a bilinear correlation between temperature and the natural frequency of the bridge [8]. Green et al also suggested machine learning based system identification of dynamical system scheme and showed that the proposed method performs well to predict the Tamar bridge's traffic-dependent behavior [9]. However, the machine learning applications in bridge management are still very limited, and especially researchers rarely spent research efforts on the application of machine learning techniques to evaluate structural damages.

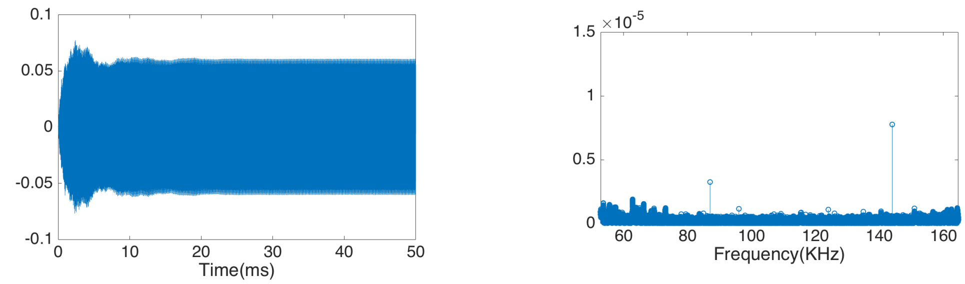
3 Data set and features

The fatigue crack sensor system consists of two exciters and sensor(s), and the exciters creates high and low frequency wave, respectively [4]. Once the exciters creates wave propagation, the sensor measures time-series vibration data as described in Figure 1 (a). The sampling rate is 1.0 MHz and the sampling duration is 0.5 second per an excitation event. For excitation, six frequency values ranged from 180 kHz to 185 kHz are used for high frequency (HF) excitation, while a single frequency (45 kHz) is used for the low frequency (LF) excitation. Nine steel specimens are prepared where five of them are intact and four of them are damaged. In addition, two sensors are installed for each specimen. As a result, I have 108 data sets as calculated by Equation (1).

$$6\ (\mathrm{HF}) \times 1\ (\mathrm{LF}) \times 9\ (\mathrm{specimen}) \times 2\ (\mathrm{sensor\ per\ specimen}) = 108 \qquad (1)$$

In this project 72 data sets serve as the training set and the rest 36 data sets are used for testing trained models.

I prepared four different feature combinations that have potential to represent damage state of specimens, and pre-processed the data to extract those features. For the first feature sets, the raw time-series data is discretized into 1, 2, 5, and 10 buckets, and the mean, standard deviation, maximum, and minimum amplitude are calculated for each bucket. The time-series data is also transformed into frequency domain, as shown in Figure 1(b), to extract features from the distribution of frequency contribution for the second, third and fourth feature combinations. The selected feature combinations are described in Table 1.



(a) Time-series data (b) Frequency domain data

Figure 1: An example of data set collected by fatigue crack sensor

Table 1: Selected feature combinations

Set No.	Features
Set 1	μ, σ, max. and min. of time-series data
Set 2	Frequency amplitude at the HF, LF, and HF-LF excitation frequencies
Set 3	max. and σ of amplitude for the frequency smaller than LF
Set 4	max. and σ of amplitude for the frequency larger than LF but smaller than HF

* μ: mean, σ: standard deviation, max: maximum, min: minimum

4 Support Vector Machines

The problem defined in this project has exactly two target classes (intact and damage), and it means that a supervised binary classification method is needed to solve the problem. Support Vector machines (SVMs) are one of the most powerful supervised learning algorithm classifying labelled data. For the separable data set, SVMs find the best hyperplane that separate all data points into the currect classes with the largest margin [10]. Finding the best hyperplane can be described as an optimization problem as Equation (2), whose solution gives the optimal margin classifier.

$$\min_{\gamma,\omega,b} \frac{1}{2}\|\omega\|^2, \qquad \text{s.t.} \;\; y^{(i)}\left(\omega^T x^{(i)} + b\right) \geq 1, \qquad i = 1, \dots, m \tag{2}$$

The optimization problem in Equation (2) can be described as a Lagragian as Equation (3),

$$\mathcal{L}(\omega, b, \alpha) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{m} \alpha_i [y^{(i)}\left(\omega^T x^{(i)} + b\right) - 1] \tag{3}$$

where α_i is Lagrange multipliers. By minimizing Equation (3) with respect to ω and b, we can obtain the dual optimization problem as described in Equation (4), which is computationally simpler to solve than the primal problem.

$$\begin{gathered} \max_{\alpha} W(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{m} y^{(i)} y^{(j)} \alpha_i \alpha_j < x^{(i)}, x^{(j)} > \\ \text{s.t.} \qquad \alpha_i \geq 0, \qquad i = 1, \dots, m, \qquad \text{and} \qquad \sum_{i=1}^{m} \alpha_i y^{(i)} = 0 \end{gathered} \tag{4}$$

Instead of using the input attribtues $x^{(i)}$ in Equation (5), we can map the attributes to some new set of quatities $\phi(x) \in R^N$, which called feature mapping. Given a feature mapping ϕ, we define the corresponding Kernel to be:

$$K(x, z) = \phi(x)^T \phi(z) \tag{5}$$

Note that computing the Kernel takes only $O(n)$ times, while computing the feature mapping $\phi(x)$ explictly take $O(n^2)$. This is called “kernel trick”, and it makes applying SVMs in high dimensional feature space very efficient.

For the non-separable data set, SVMs can use a soft margin that permits some data point have functional margin less than 1. In other words, the hyperplane now do not necessarily separate all data points currectly [10]. The optimization problem for the non-separable case is described in Equation (6), where ξ_i is slack variable and C is a penalty parameter.

$$\min_{\gamma,\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m}\xi_i$$
$$\text{s.t.}\ \ y^{(i)}\left(\omega^T x^{(i)} + b\right) \geq 1 - \xi_i, \qquad \xi_i \geq 0, \qquad i = 1, \dots, m \tag{6}$$

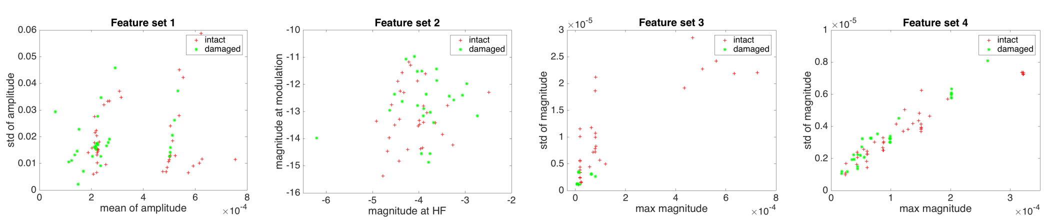
In addition, we can also derive the dual problem for Equation (6) as described in Equation (7).

$$\max_{\alpha} W(\alpha) = \sum_{i=1}^{m}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{m} y^{(i)}y^{(j)}\alpha_i\alpha_j < x^{(i)}, x^{(j)} >$$
$$\text{s.t.} \qquad 0 \leq \alpha_i \leq C, \qquad i = 1, \dots, m, \qquad \text{and} \qquad \sum_{i=1}^{m}\alpha_i y^{(i)} = 0 \tag{7}$$

5 Experiment result and discussion

Due to the lack of prior knowledge of the relation between features and target, I tried different kernels including linear kernel, quadratic kernel, and Gaussian kernel. Since the given data set is not guaranteed to be separable, the box constraint *C* is defined. I firstly set *C* as a large value (e.g. 10) and continuouly decrease it to get better training accuracy. The result shows that the training accuracy is highest when *C* is 1. The *k-folds* validation is implemented to prevent over fitting. I used *k=10* folds which is a typical choice for *k*. The primary metrics in the training stage are the high training accuracy as well as small false-negative ratio, because the ultimate goal of this project is to evaluate damage of bridge structure, where a certain level of safety margin is desirable while false-negative evaluations may lead very disastrous result along with a great loss to the society.

Firstly, the data point distributions of each feature set are plotted in Figure 2 to choose the most appropriate feature set. Figure 2 shows that the feature set 3 has significant trend that divides the damaged set from the intact sets. The training accuracy for each feature set can also be found in Table 2. Figure 3 shows the ROC curves and confusion matrices of SVMs using linear, quadratic, and gaussian kernel with the feature set 3, and the corresponding training accuracy can be found in Table 2. The training results indicate that the SVM with the quatratic kernel has the best results in terms of the defined metric - training accuracy and false-negative ratio.

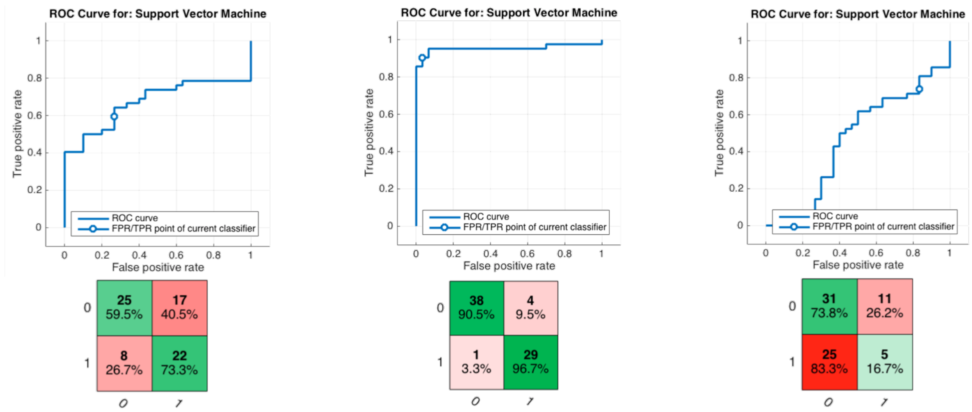


(a) Feature set 1 (b) Feature set 2 (c) Feature set 3 (d) Feature set 4

Figure 2: Data point distribution of each feature set

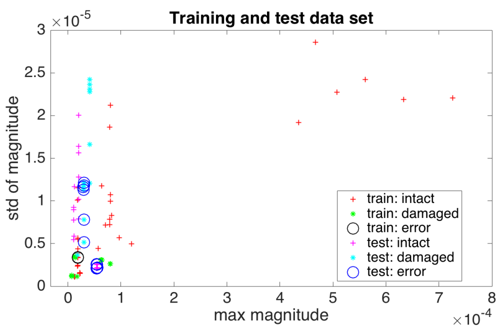
Table 2: Training accuracy of SVMs

Set No.	Linear kernel	Quadratic kernel	Gaussian kernel
Set 1	70.8%	72.2%	58.3%
Set 2	66.7%	68.1%	58.3%
Set 3	65.3%	**93.1%**	50.0%
Set 4	52.8%	68.1%	50.0%



(a) Linear kernel (b) Quadratic kernel (c) Gaussian kernel

Figure 3: ROC curves and confusion matrices of SVMs (Training set)



(a) Data point distribution

True \ Prediction	Intact	Damaged
Intact	12 (66.7%)	6 (33.3%)
Damaged	6 (33.3%)	12 (66.7%)

(b) Confusion matrix

Figure 4: Data point distribution and confusion matrix (Test set)

In the test stage, the trained SVM model using the quadratic kernel and feature set 3 is evaluated based on the test data set. Figure 4 describes the distribution of data point of entire data set and the confusion matrix for the test set. Unfortunately, the test accuracy is much poorer than the training set and the false-negative ratio is also unacceptable. One of the main reason of this high variance problem would be the insufficient data points, since only 108 data points are used in this project. Another typical way to settle the high variance problem is to reduce the number of features, but the number of features used for the test is not very large, so that the feature-reducing scheme is not applicable here. Rather, it might be worth a try to define different feature sets based on the additional prior knowledge about the correlation between wave propagation properties and damage states.

6 Conclusion

In this study, a machine learning based fatigue crack evaluation method is proposed. Sets of wave propagation data collected by fatigue crack sensor are prepared for the training and test data, and DFT is performed to extract meaningful information from the raw data. SVMs are applied to solve the classification problem distinguishing damaged and intact specimen, and the quadratic kernel function shows better result than other kernels. The proposed method performs well for the training set, while the trained model result in an inaccurate classification result for the test data set. In the future work, I will prepare more data set and try different features to reduce high variance, and thus, improve the proposed method.

Acknowledgments

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