STRUCTURE HEALTH MONITORING IN EXTREME EVENTS FROM MACHINE LEARNING PERSPECTIVE

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ABSTRACT
Structure health monitoring utilizes the statistical signal information gathered from sensors implemented on structures to detect the building behavior. This information is more accurate and easier to analyze than traditional structural analysis method, which detects the building damage using dynamic properties directly. In this project, acceleration time history records of a Benchmark structure subjected to certain excitations obtained from sensors on the structure were analyzed, several Damage Sensitive Features were extracted, and different machine learning algorithms were used to predict the future behavior of the structure in extreme events like earthquakes.

KEYWORD
Structural Health Monitoring, Seismic Analysis, Damage Detection, Machine Learning

INTRODUCTION
Structural health monitoring is becoming a hot topic in the recent decades because it provides engineers with information about the building damage and characterization strategy by analyzing data obtained from the monitoring sensors installed on structures. In the past, people have been focusing on detecting the building damage using dynamic properties such as frequencies and mode shapes, and performing nonlinear structural analysis directly. However, these methods are not sensitive to minor damage or local damage and they are extremely computationally expensive and time consuming. In contrast, detection technologies that utilize statistical signal information are more accurate and easier to implement. Thus in this project, analyzing the structural seismic behavior data using different machine learning algorithms was focused on so as to predict the behavior of the structure in future extreme events.

METHODOLOGY
The general statistical pattern recognition procedure used for building health monitoring can be summarized in the following four steps: operational evaluation, data acquisition, feature selection and statistical modeling for future discrimination. Since structural damage affects the dynamic properties of the structure, which will change the statistical characteristics of the measured acceleration time histories, the training data used in this project were chosen to be the acceleration time histories of the structure under different damage states (undamaged and damaged). The data generation followed the paradigm mentioned above and the data was obtained from simulating a four-story, two-bay by two-bay steel-frame quarter-scale model structure. Total 16 sensors were located on 4 columns at each floor and each sensor measured acceleration response in two translational directions during different loading events. Several Damage Sensitive Features (DSFs) were then extracted from those time history records at different locations under different damaged states subjected to different excitation sources. These DSFs represent the dynamic behavior of the structure, which varies according to the damage state of the structure. Two damaged states of the structure were included in this study and they were combined to be labelled as “damaged” as opposed to the “undamaged” case. The combined

damaged states were defined as removing all the braces from 1st and 3rd floors, resulting in a 71% stiffness loss in y-direction at each floor (as the excitation is in y-direction). This means that only the major damage was characterized as damaged state, ensuring the data associated with the damage states being more separable. Statistical models using different machine learning algorithms were then developed to be used for future damage categorization. Each algorithm was trained and the probability of errors was evaluated on the validation set.

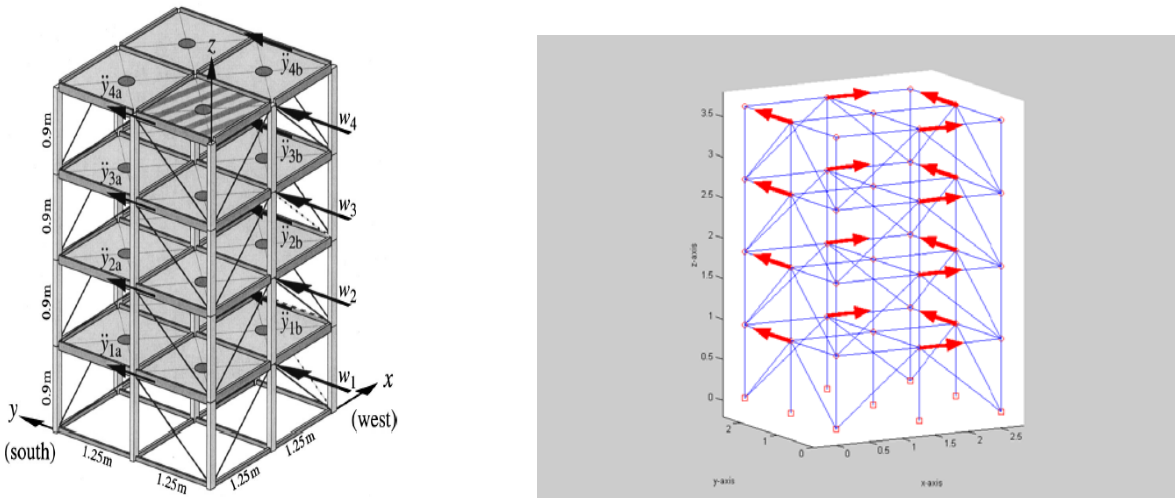

Fig. 1 Sensor location and recorded directions

DATA GENERATION AND FEATURE SELECTION

The data generation program, ‘datagen’, was obtained from the website of the IASC-ASCE SHM Task Group. In the simulation, the excitations were modeled either as the independent filtered Gaussian white noise or the direct shake at the roof level. Nonlinear structural time history analysis was performed to get the acceleration time histories using Nigam-Jennings integration method with a damping ratio of 2% and a noise level of 10.This method decomposed the structural system into its modal space, integrated each mode assuming the excitation was piecewise-linear over a time step, and superimposed to get the time history responses. The acceleration data sets used in this project were then generated using different random seeds using the ‘datagen’ program in Matlab. The typical acceleration time history data is shown below in Fig.2. In this project, the acceleration records generated last for 700s with a time step of 0.001s, thus the acceleration data has 700,000 rows and 16 columns, which represent the 16 different locations of the sensors.

Yet, if the raw data were used directly as the input matrix, a high variance problem would rise as a result of over-fitting. Also, acceleration time history itself could not directly represent the damage-related behavior of the structure. Thus, to preprocess the data, several damage sensitive features (DSFs) were extracted by fitting an optimal autoregressive (AR) model with an order of 8 to each time history record, which was the smallest order that could be used to achieve a stable behavior. AR coefficients obtained from this model could directly represent the natural frequencies of the structure in various damage states, thus these coefficients could be combined to compute the Damage Sensitive Features (DSFs), which could most effectively represent the seismic behavior of the structure.

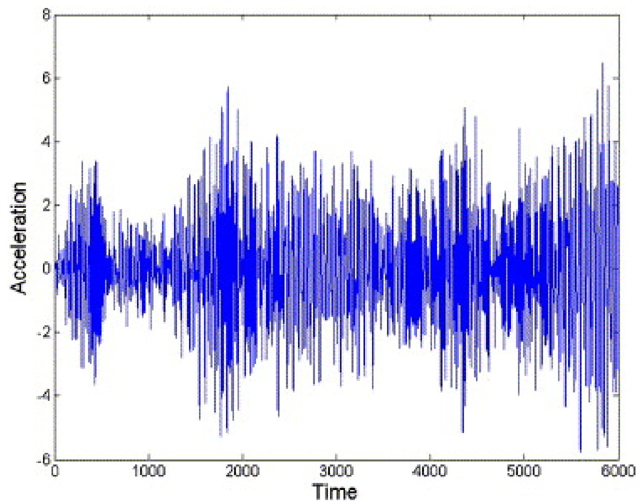

Fig. 2 Typical Raw Acceleration Time History Record from an Undamaged Case

Each acceleration time series was divided into 100 segments with each segment containing 7000 data. The data per segment was then normalized and an optimal AR model with an order of 8 was fitted to the model and the corresponding coefficients were obtained using Matlab built-in function "arbug". DSFs were then computed as functions of AR coefficients, with the number of DSFs and orders of coefficients determined by a forward search algorithm. Three basic DSFs, which are functions of the first three AR coefficients for each segment per acceleration time history, were included in this model:

$$DSF_i = \frac{\alpha_i}{\sqrt{\alpha_1^2 + \alpha_2^2 + \alpha_3^2}}, (i = 1, 2, 3)$$

The logarithmic combinations of the first and second DSFs were also used as the other two features. Furthermore, the floor level and location of the sensors at each floor level, and the shake sources (either independent filtered Gaussian white noise or direct shake at the roof), were also selected to be the other three features. Different random seeds were used to generate acceleration data at each location 10 times for one undamaged and two damaged states respectively, and then the DSFs were computed accordingly. Thus, the inputs have 8 features in total, with total 48,000 data sets for training. (m=48,000, n=8.) To better use these data to train the models, 5000 samples were randomly selected from these data sets several times and the results were averaged. The response of the model was categorized using two labels: damaged or undamaged. Following the similar procedures, test sets with 8000 testing examples in total were obtained.

ALGORITHM DESCRIPTION

Because this problem is a binary classification problem, several classification algorithms were selected as potential candidates.

Naive Bayes was first tried for a quick start because it was easier and faster to implement compared to other methods. A uniformly distributed prior was used for the damage states and Naive Bayes algorithm was performed in Matlab using the Naive Bayes class. The results indicated fairly large training and testing errors of 45% and 33%, respectively. Yet the performance of the algorithm could not be further improved efficiently by adding more features, which implied there were issues with the model itself as we had a high bias problem. This was because the prior distribution used in this model might not be appropriate. However, trying multiple of other distributions for the prior could not significantly improve the results, indicating more studies need to be done on the damage states definition so as to come up with more suitable and case-specific prior distribution for applying the Bayesian algorithm.

As the DSFs are approximately Normal distributed, the Gaussian Discriminant Analysis was then used and a multivariate Normal distribution was fitted to each 100 sets of features per acceleration and the mean and covariance matrix were computed for undamaged and damaged states. The training and testing errors were 22% and 24%, which were better than those from the Naive Bayes model. Also, by computing the KL divergence of the probability density functions of the features with undamaged and damaged states, a threshold of the KL value was obtained. The structure can be classified as damaged if this value has been exceeded. However, this method requires a larger set of data then those data previously described to get an optimal threshold (the data in this case needs to be grouped for each acceleration record). As a consequence, the training and testing error obtained using this method were fairly large: 32.1% and 33.4%.

Logistic Regression algorithm and Support Vector Machine (SVM) algorithms were then tried to classify the damage state of the structure in the next step. Matlab toolbox and Liblinear-1.94 package were used and surprisingly errors associated with SVM were large (30% and 33% for training and testing respectively), while Logistic Regression model gave a relatively smaller training and testing error of 15% and 16%. Different kernels for SVM were tried, and the training and testing errors were successfully reduced after conducting the kernel and feature selection (the Gaussian Kernel gave the best results), yet still Logistic Regression Model performed much better.

To further develop a better model, Neural Network algorithm with 10 hidden neurons and 2 output layers was used to train a model. The neural network algorithm was implemented in Matlab using nprtool. And the network was trained to classify the inputs according to the labels using scaled conjugate gradient backpropagation. In structural engineering practice, engineers are more interested and concerned about minimizing the mislabeling error associated with the case when damaged state is mislabeled as undamaged state. The confusion matrix indicated this mislabeling error was as low as about 5% for both training and testing. Other network layouts were tired with different number of hidden neurons, some generated fairly small total errors, but with higher error for damaged misclassified as undamaged. Thus, even the total error was relatively larger; the 10 hidden neurons layout was chosen to be the optimal model as the interested error was the smallest.

The table below summarizes the training and testing errors for all the models used in this study.

Result Summary		
Model	Training Error	Testing Error
Logistic regression	15%	16%
SVM	30%	33%
GDA	22%	24%
Naive Bayes	45%	33%
Neural Network	21%	22%

DISCUSSION AND CONCLUSION

Lots of features were included at first, resulting in a high variance problem in the model. By engaging only the appropriate damage sensitive features, the model seemed to have a high bias problem; yet adding more features could not really resolve this issue because of the complex property of DSFs. However, the best training and testing performance was achieved using 8 features, which could generate relatively accurate results.

As in this problem, the prior of the damaged states were difficult to define; using only a uniform distribution to estimate the prior was not accurate enough, thus errors in Naive Bayes model using uniform priors were fairly large. As in real life, the damage situation is hard to describe with the lack of the statistical data, more studies on describing the prior distribution of the damage state are needed before more accurately using the Bayesian algorithm.

The results indicate that the Logistic Regression Model and the Neural Network Model were capable of generating the best performance, and thus are recommended for future prediction of the health performance of the structure in extreme events, such as earthquakes.

FUTURE OBJECTIVES

When including the data associated with a minor damage state, i.e. just removing the braces from one floor, it turned out that the data were barely separable and the training and testing errors were both very high. Thus one of the next steps in the future is to find out how to describe this more complicated situation and engage more specific major and minor damage states, i.e. revise the labels to 1-6 damage states. Features that are more sensitive to structural damages could be discovered following structural experiment testing and more algorithms could be tried in the future to come up with better machine learning models.

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