IMPLEMENTING MACHINE LEARNING IN EARTHQUAKE ENGINERING

CS 229 Machine Learning, Autumn 2016 Poster Presentation

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INTRODUCTION

The use of accelerometers in earthquake engineering is very important for engineers as it helps them understand and quantify the magnitude of seismic forces. Structures are typically instrumented at the ground and floor levels; thus, when an earthquake occurs, the ground and floor accelerations are recorded. This data can then be used to understand the performance of the structure and it allows engineers to create prediction models to design future ones.

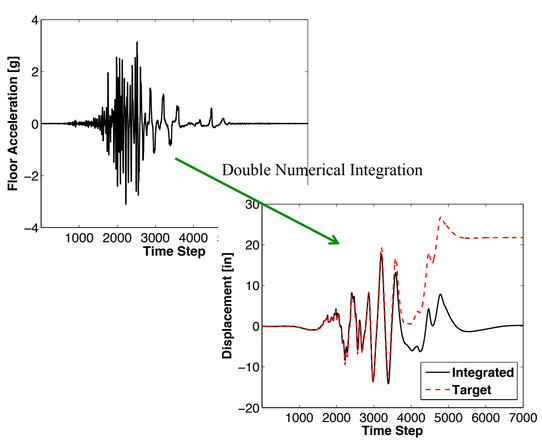
Motivation:

A measure of structural performance is the amount of **displacement, *x(t),*** a structure experiences during an earthquake. The higher the displacement, the more damage the structure sees.

$$x(t) = \int\int x(t)\,dt\,dt = \sum\sum \ddot{x}(t)\,\Delta t \Delta t$$

The displacement can be typically derived by double integrating the **acceleration,** $\ddot{x}(t)$. Nevertheless, this process is not trivial as the data requires pre-processing (e.g., baseline correction and blind filtering) to obtain reasonable results.

As seen below, residual displacements are not well captured from the acceleration data.

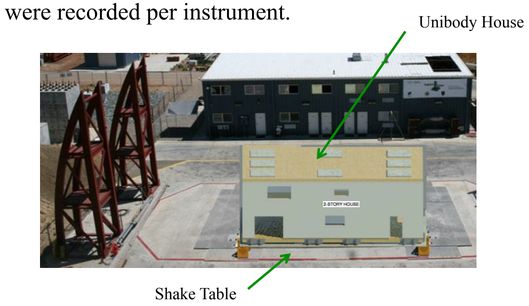


OBJECTIVE

- Apply machine learning to acceleration data to obtain displacement data
- Compare its results to double integration method

DATA

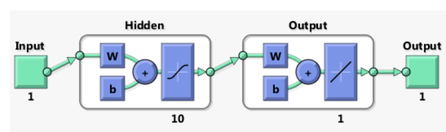
Data was obtained from the experimental results of a 2-story wood-frame Unibody house. The structure was tested on an earthquake simulator or shake table. The 1989 Loma Prieta Earhtquake (GM) was simulated at seven amplitudes. Each floor was instrumented with five accelerometers. The displacement was measured with string potentiometers. A total of 12,000 data points were recorded per instrument.



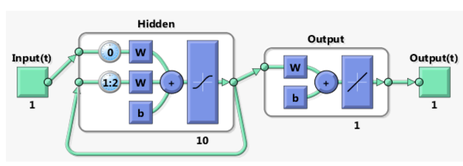
ML Implementation

Neural networks were investigated in this project using Matlab libraries. Since these are time sequences, Feedforward Neural Networks (FFNN) and Recurrent Neural Networks, respectively, were particularly implemented.

FFNN



RNN



ML FEATURES

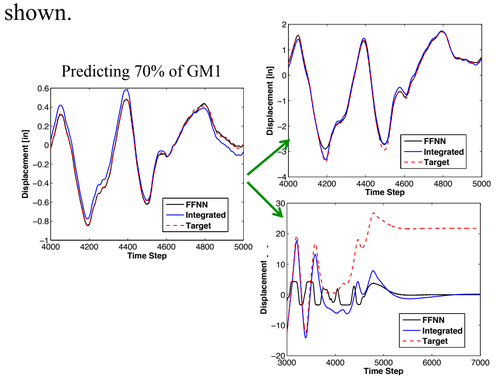
Eight features were considered for this project. These features were selected based on data that can be collected from an earthquake. These features were:

Building	Earthquake
Acceleration at floor of interest	Acceleration of the ground
Vertical acceleration of floor of interest	Ground displacement (derived from acceleration)
Power spectral density of horizontal acceleration	Vertical acceleration
Ratio of Fz floor / Fz ground	Power spectral density of ground acceleration

The total amount of features used were six. The ones in red were not used as they added noise to the output.

RESULTS

Data trained with 30% of GM1 and used to predict the behavior at higher intensities. Small windows of these predictions are shown.

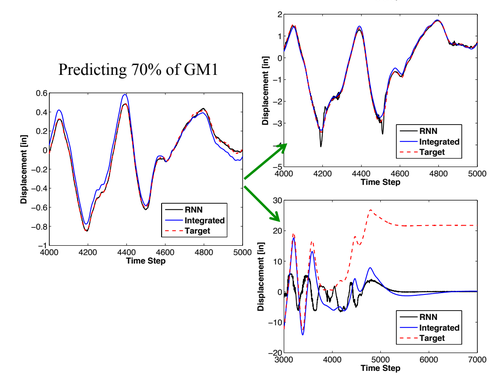


Predicting GM6

Does a fairly good job, sometimes not capturing the peaks.

Predicting GM7

Does not do a good job at picking up peaks or residual displacement



Predicting GM6

Does a fairly good job with a bit more noise

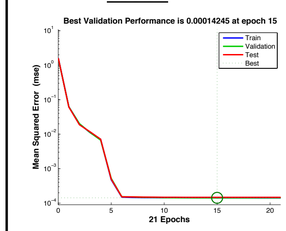
Predicting GM7

Does not do a good job at picking up peaks or residual displacement

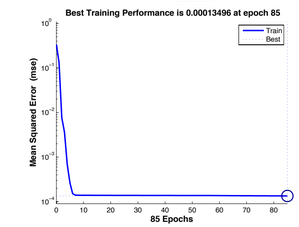
RESULTS

Looking at the performance, the RNN has better performance but takes longer to train and the predictions are not always as smooth.

FFNN



RNN



It was noticed that if the data was trained multiple times for the same neural network, different performance training weights were obtained.

CONCLUSIONS

•Neither neural network was able to pick up the residual drift of GM7.

•For both NN, 30% percent of 12000 points for the smallest magnitude earthquake was sufficient to predict a good portion of the rest of the GMs with good accuracy. More training epochs and data should be implemented to see if better performance is reached

•Results also suggest that features need to be selected carefully to avoid noise in the target output. The ground displacement was an important feature.

•Double numerical integration is still a more practical way to compute the displacement from accelerations as it takes less time than training neural networks.

FUTURE WORK

This was just a preliminary study incorporating machine learning to this problem, which arose from the interest of the author. More research is needed before discarding neural networks as a possible method to pick up residual displacements. More data (either experimental or simulated) should be used to generalize the model and check if performance is improved.

ACKNOWLEDGMENTS

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