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Analyzing Ground Motion Records With CVI Fuzzy ART

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***Abstract*—This paper explores using Cluster Validity Indices Fuzzy Adaptative Resonance Theory (CVI Fuzzy ART) to cluster ground motion records (GMRs). Clustering the features extracted from a supervised network trained for predicting the structure damage results in less overfitting from the trained network. Using Cluster Validity Indices (CVIs) to evaluate the clustering gives feedback to how well the data is being classified, allowing further separation of the data.**

By using CVI Fuzzy ART in combination with features extracted from a trained Convolutional Neural Network (CNN), we were able to form additional clusters in the data. Within the primary clusters, accuracy was improved from our previous best of 82% [1] up to 95% accuracy. Additionally, the ~20% of the data that ended up in secondary clusters was identified as borderline data, highlighting that the result is unstable, and that the more severe class should be considered despite the simulation results.

***Keywords*— Adaptive Resonance Theory, Clustering, Earthquakes, Ground Motion Records, Machine Learning, Neural Networks**

I. Introduction

Seismic damage evaluation is a critical part of loss and recover assessment after earthquakes [1]. Traditional statistics-based fragility curves have been widely used to estimate the probability of structural damage states under certain earthquake intensities over the past two decades [2]–[6]. However, limitations of statistics-based approaches such as the prior assumptions of statistical distributions [7] and insufficient intensity measures [8] could introduce considerable errors in seismic damage evaluation. To address these limitations, extensive studies have been conducted to develop machine learning (ML)-based surrogate models for the traditional fragility curves. For example, studies of [9]–[11] etc. estimated the seismic damage of reinforced concrete buildings based on neural networks with multiple intensity measures as inputs and achieved rapid, accurate predictions of seismic-induced structural damage. Researchers, e.g. [8], [12]–[14] etc. applied ML models on highway bridge structures and nuclear plants for seismic demand analyses and achieved satisfying performance. ML-based models for portfolio seismic damage evaluation could also be found in the studies of [15], [16]. These and related studies showcase the feasibility of ML methods. This paper discusses how to make them more practical.

ML surrogate models can be categorized into two types: the regression model to estimate seismic engineering demand and the classification model to classify the structural damage state. In this study, we focus on the limitation of neural-networks-based classification models. In the classification application, ML models will predict the damage state of corresponding structures, e.g., Light, Moderate or Severe. One limitation in such classification is that it is observed in [9], [10] that misclassification tends to happen on the samples whose damage states are intermediate compared to other damage states. For instances, when three damage states are considered, samples of Moderate damage states have lower recall and precision than the other two damage states of Light and Severe.

In this study, a powerful ML technique, unsupervised learning, specifically clustering using Adaptive Resonance Theory(ART), is proposed to address this limitation of ML seismic models. Unlike the existing ML models which are trained by pre-labeled samples via time history analyses (THA), clustering solves the classification problem by looking at similarities in the individual samples, and determining the labels based on this similarity. These techniques allow for a diverse range of information to be extracted from the data, though at the cost that very fined tuned adjustments are needed to control which information is extracted. Cluster Validity Indices Fuzzy Adaptative Resonance Theory (CVI Fuzzy ART) [17], [18], solves most of this problem by using Cluster Validity Indices (CVIs) to determine if more or less clusters are needed. The estimate of the number of clusters, and selection of best hyperparameters are key weaknesses of most unsupervised learning approaches. Using CVIs mitigates these problems, especially when more than one CVI is used.

Another problem is extracting the correct features from the dataset. High dimensionality data is particularly difficult for clustering, as the data will be too sparse to accurately determine the similarities. This study utilizes convolutional neural networks (CNN) to automatically extract the feature (based on our previous work [19].) Then, the latent features will be input into the CVI Fuzzy ART model for clustering.

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II. Experiment Design

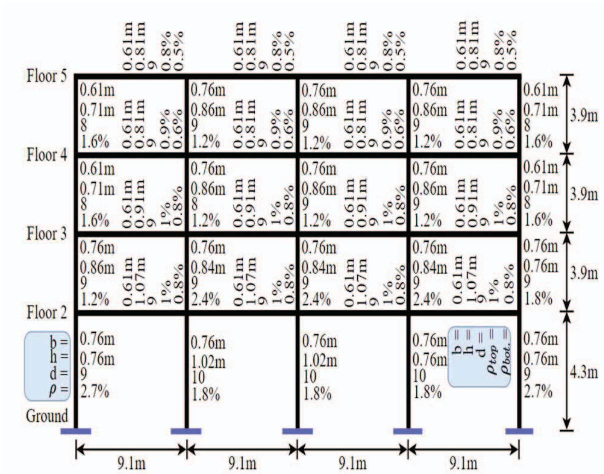

Figure 1 The fixed-base benchmark r/c frame with beam and column design information

A. Data generation

This study uses the same dataset as in [19], [20]. The CNN were trained for a code-conforming benchmark reinforced concrete building design [21], The perimeter frame schematic of the four-story building is shown in Figure 1. The size of beams and columns and reinforcement information are also given, where 'b', 'h', and 'd' are the width (m), depth (m) and rebar diameter (mm) of beams and columns. 'ρ' is the reinforcement ratio of columns. 'ρbot' and 'ρtop' are the bottom and top reinforcement ratios of beams. The structural model is modeled in OpenSEES [22] to conduct nonlinear THA to obtain the structural responses under earthquakes.

After the structural model is determined, ground motion records (GMR) are needed for the nonlinear THA. In this study, GMRs are mainly from two sources: the instrumental records of past earthquake and synthesized records. The instrumental records are mainly downloaded from database of the Pacific Earthquake Engineering Research (PEER) Center (https://ngawest2.berkeley.edu/). The synthesized method is based on the development in [23]. Then these historical and synthesized records are scaled from 1 to 10 according to the scale factors used in [21], [24], to generate sufficient strong-motion records. Finally, a balanced dataset of 3,201 records is filtered as the input data to our model, among which 1,067 GMRs cause Light damage, 1,067 GMRs cause Moderate damage, and 1,067 GMRs cause Severe damage to the benchmark structure, respectively.

B. Data Preparation

Each record in our dataset contains 3 feature vectors, Displacement, Velocity, and Acceleration, with 10,000 samples. The Velocity and Acceleration vectors were discarded, and a CNN was trained to predict the resulting class. The latent space of the CNN is then fed into a TSNE model to further reduce the dimensionality.

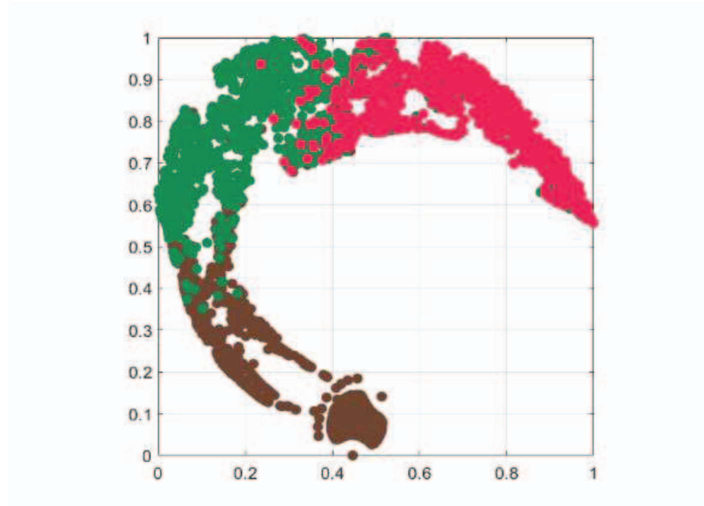

Figure 2 Data visualization using TSNE to reduce the dimensionality of CNN latent space. Colors represent different ground truth labels.

III. Results

A. K-means

As a baseline test K-means clustering was used to classify the data into 3 categories, which resulted in 85% accuracy. This slightly outperforms the trained CNN which achieves 82% accuracy on the validation data, mostly due to the CNN overfitting the data. This result is expected as the final layers of the CNN are performing a similar task of separating the latent space into classes.

B. CVI Fuzzy ART

To analyze the data in more detail, we used CVI Fuzzy ART. Several simulations were run with random sample order. ART doesn't need the number of clusters as an input, and by using CVIs the hyperparameters can be adjusted automatically to achieve better clusters. CVI fuzzy ART generally returned 5-8 clusters, with the best results reaching 90% accuracy over the entire dataset, or the 3 main clusters reaching 95% accuracy, though only on about 80% of the data. The remaining 20% of the data was near cluster boundaries. For this application, we recommend classifying them more conservatively in the more severe category.

IV. Conclusion

By using CVI Fuzzy ART to cluster the latent space of a supervised system we were able to achieve better classification accuracy than the original supervised method. In addition to the better performance, some interesting conclusions can be made due to how the clusters ended up behaving. The clearly defined regions of overlap can be double checked for mislabeled data, and more specific defining features. Due to safety considerations, the overlapping regions could be treated as the more severe case to ensure the safety of the structure. These additional metrics that can be used allow for a much more flexible system that can be better fit the problem being addressed.

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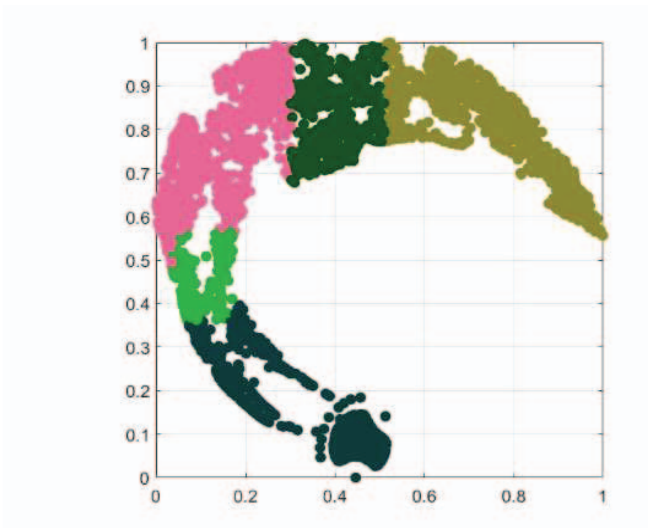

Figure 3 Visualization of clusters generated by CVI Fuzzy ART

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