An Unsupervised Machine Learning Approach for Damage Assessment in Structures

教師なし機械学習を用いた建築構造物の損傷評価手法の検討

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This paper presents an unsupervised machine learning approach for damage assessment in building structures. A large dataset was created from a verified numerical simulation of a large-scale shaking table experiment (E-Defense). The numerical simulation was automated to generate a large dataset automatically. The variables in each simulated case were location of damage and level of damage. The first three modal frequencies were collected from each case and later input to a Gaussian mixture model (GMM) for clustering. The GMM model was able to create clusters autonomously based on the level of damage and direction in which damage occurred to an extent.

This approach shows the importance and applicability of creating large datasets and utilizing unsupervised learning for damage assessment.

Keywords: Machine learning, Natural frequency, Gaussian mixture model, Damage assessment, Numerical simulation

本報では，教師なし機械学習を用いた建築構造物の損傷評価手法について検討した。まず，E-ディフェンスにて実施された 3 階建て構造物の振動実験に対応する解析モデルを構築し，数値シミュレーション結果と実験結果を比較することで，解析モデルの妥当性を検証した。次に，この解析モデルを基に，損傷位置および損傷レベルを変数とした数値シミュレーションを自動化し，大規模な機械学習用データセットを構築した。最後に，各シミュレーション結果から抽出した 1 次から 3 次の固有振動数に対して，ガウス混合モデル（GMM）によるクラスタリングを適用した。その結果，GMM モデルにより損傷の有無および程度を自動的に評価可能であることが示唆された。

キーワード：機械学習，固有振動数，ガウス混合モデル（GMM），損傷評価，数値シミュレーション

1. Introduction

Damage assessment plays a pivotal role in structural health monitoring for structural integrity and public safety. Early and reliable identification of damage and its intensity can prevent catastrophic failures and reduce maintenance costs. Recently, machine learning and deep learning are extensively used for damage assessment[1), 2)]. However, in many real-world applications, the availability of labeled data that distinctly represents damaged and undamaged states is limited or nonexistent. This limitation highlights the need for unsupervised machine learning techniques that can autonomously learn the underlying structure of data without requiring predefined labels[3)]. Among the various unsupervised approaches, Gaussian mixture models (GMMs) provide a powerful probabilistic framework for modeling and clustering complex data. GMMs assume that observations are generated from a mixture of several Gaussian

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distributions, each representing a latent cluster within the data [4].

In this study, unsupervised GMM clustering is leveraged for damage detection in structural systems. By inputting the first three modal frequencies as a mixture of Gaussian components, it is aimed to automatically distinguish between normal and potentially damaged conditions without requiring prior labeling of the data. To determine the appropriate number of clusters that best represents the structural states, Bayesian Information Criterion (BIC) is employed, which balances model fit and complexity. This approach offers an interpretable, data-driven solution for identifying anomalies that may indicate damage, even in the absence of labeled examples. To verify the approach, experimental data from a shaking table experiment of a three-story building, conducted in Hyogo Earthquake Engineering Research Center (E-Defense experiment) and simulation data of the verified numerical model of that experiment was used. As in the field of Structural Health Monitoring, obtaining data from actual structures, especially in case of damage states, is extremely rare so numerical simulation can provide a viable alternative to generate data. Furthermore, automation algorithm was created to run a large number of simulations continuously to create a large database of numerous damage conditions.

2. Brief introduction to the E-Defense experiment

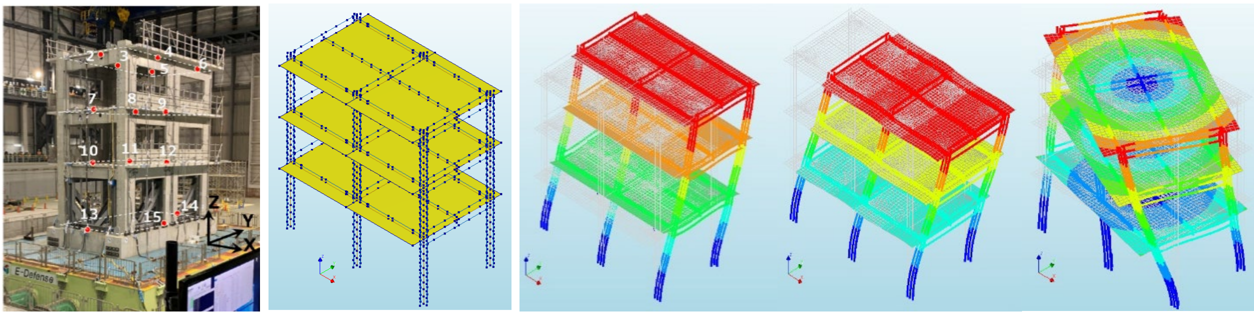
For this study, experimental data is used from a full-scale 3-story building tested on E-Defense, which is a large-scale shaking table in Japan, as shown in **Fig. 1**(a). The details of the experiment are reported by Yeow et al.[5]. Artificial earthquake waves were input based on a reference shaking acceleration (1.0-scaled excitation) that fit to the 5% damped acceleration response spectrum referred to "extremely rare earthquake motion" in Japanese Building Standard. During the experiment, the structure experienced 0.2-scaled excitation, 1.0-scaled excitation, 1.5-scaled excitation (twice), and 1.6-scaled excitation at various times. Throughout the experiment, continuous ambient acceleration data was recorded[6]. The layout of the sensors is shown in **Fig. 1**(a). The properties of concrete and D19 reinforcement bars mainly used in the building are shown in **Table 1** and **Table 2**, respectively.

Table 1. Properties of concrete

Story	Compressive strength	Modulus of elasticity
1F-2F	47.1 MPa	32.1 GPa
2F-3F	44.1 MPa	33.5 GPa
3F-RF	37.4 MPa	29.4 GPa

Table 2. Properties of D19 reinforcement bars

Yield stress	379 MPa
Tensile strength	567 MPa
Young's modulus	193 GPa
Yield strain	2.0×10^{-3}



(a)Test specimen　　(b) FE model　　(c) 1st three mode shapes

Fig. 1. Full-Scale test specimen and eigen value analysis

3. Verification of finite element modelling

In this study, numerical modeling is carried out in DIANA FEA(V10.6) software. The model was created by using line elements apart from slab which was created as shell element as shown in **Fig. 1**(b). Model was generated with 1D and 2D elements instead of 3D to make computation cost low. The RC beams and columns were assigned as Class-III beam elements. Class-III beam elements use an isoparametric approach, where the displacements and rotations of the beam's axis normals are treated as independent. These are calculated by interpolating the nodal displacements and rotations. For compressive and tensile behavior, fib Model Code for Concrete Structures 2010 was used. Rayleigh damping coefficients α and β were considered as 0.2 /s and 0.002 s, respectively. The reinforcement was modeled as embedded bars by considering Von-mises plasticity. Strain hardening was also incorporated by considering total strain and yield stress values.

As a first step of model verification, the weight of the simulated model was verified. The weight of the simulated model was calculated as 1,792 kN, which was almost equal to the actual weight of the structure i.e. 1,789 kN.

3.1 Eigenvalue analysis

An Eigenvalue analysis was performed to determine the eigen frequencies and corresponding mode shapes. Whereas fast Fourier transform (FFT) technique was employed to determine the experimental natural frequencies from the recorded ambient vibration data.

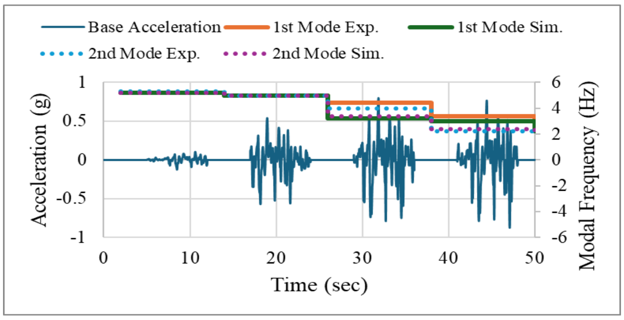
The first three eigen frequencies obtained from simulation were 4.7 Hz, 5.0 Hz and 6.4 Hz, respectively. Whereas the first three experimental natural frequencies were 5.2 Hz, 5.3 Hz and 7.2 Hz, respectively. The difference in the simulated and experimental natural frequencies was considered to be small enough for the purpose of this study. The mode shapes as shown in **Fig. 1**(c) were identical in both cases.

3.2 Structural nonlinear time-history analysis

Structural nonlinear time-history analysis was performed to verify the acceleration response of the numerical model. Base acceleration containing 0.2, 1.0 and 1.5 (twice) scaled excitation along with extremely small amplitude ambient vibrations record before and after each shaking regime was used as shown in **Fig. 2**.

Natural frequencies were verified after each shaking regime by using FFT technique on ambient vibrations response. After each shaking regime, a decline in frequences was observed. The comparison between experimental values and simulated values is shown in **Fig. 2**.

The acceleration response was also verified at each floor for 0.2 and 1.0 scaled excitation. The results for 3rd floor and rooftop are shown in **Fig. 3**. It can be observed that the acceleration response is almost 100% matched in the case of 0.2-scaled excitation. Furthermore, in case of 1.0 scaled excitation, response is almost similar up to the maximum peak acceleration, but an attenuation was observed in case of simulation results. Furthermore, experimental and simulated time period also remained almost the same.



	Modal frequencies (Hz)					
	1st Mode			2nd Mode		
	Exp.	Sim.	Diff.	Exp.	Sim.	Diff
Before Excitation	5.2	5.2	0	5.3	5.2	0.1
0.2 Scaled Excitation	5	5	0	5	5	0
1.0 Scaled Excitation	4.4	3.2	0.8	4	3.4	0.6
1.5-1 Scaled Excitation	3.4	3	0.4	2.2	2.4	0.2
1.5-2 Scaled Excitation	2.8	2.2	0.6	1.9	2.2	0.3

Fig. 2. Comparison of experimental and simulated natural frequencies

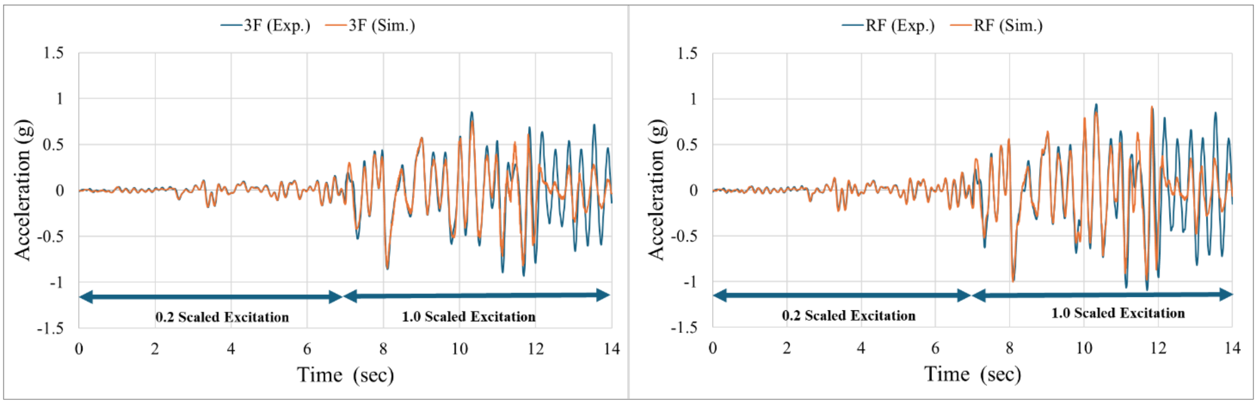


Fig. 3. Acceleration response at 3rd floor (Left) and roof top (Right)

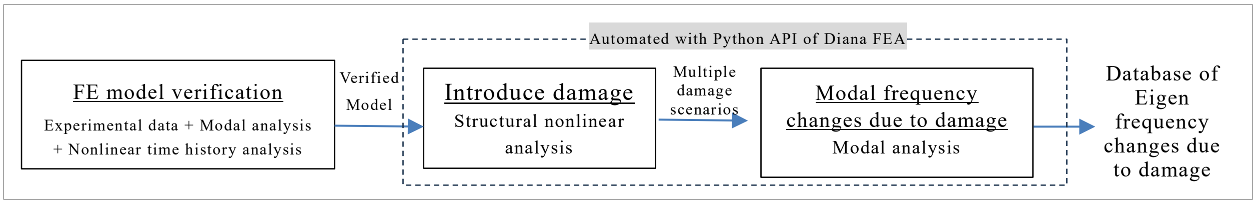


Fig. 4. Process of database creation

4. Creation of database

Flowchart of the overall process of creating database is shown in **Fig. 4**. After verification of the numerical model of the E-Defense experimental model, an automated simulation technique was devised to create a large database. Unique damage scenarios based on intensity and location of the damage were introduced to the model. To do so, 4 levels of loads were applied on a particular location to introduce different levels of damage such as fine cracks, prior to reinforcement yielding, post reinforcement yielding and close to reinforcement rupture. As there were 42 members of the model, in the first simulation regime, aforementioned damage conditions were introduced at 1 location at a time resulting in 168 simulation cases.

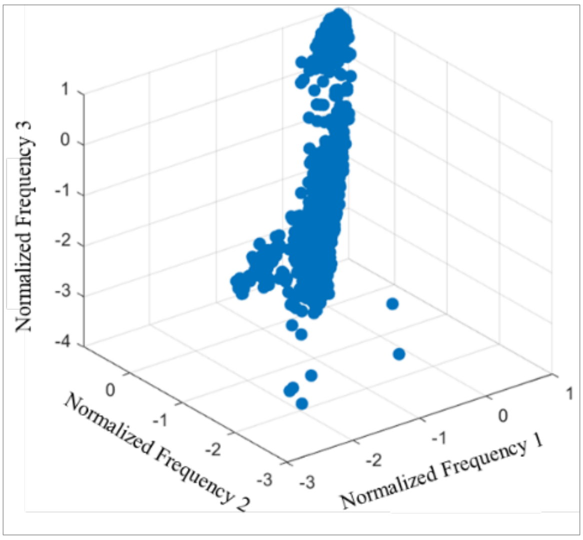


Fig. 5. Plot of database

In the second simulation regime, the damage scenarios were introduced to 2 members simultaneously. This regime resulted in 3,444 simulation cases. Consequently, a total of 3,612 simulation cases were run to generate a large database consisting of damage scenarios of varying intensities and locations. Due to the introduction of high nonlinearity through damage at multiple locations prior to the modal analysis, some analysis cases could not achieve proper convergence and therefore omitted from the database. The final database included around 2,500 cases. A plot of database is shown in **Fig. 5**. It can be observed that it is hard to distinguish between the data points without utilizing some appropriate visualization method.

It is worth mentioning that running such a large number of numerical simulations one by one may result in substantial time consumption. To counter this issue, simulations were automated utilizing the Python application program interface to run numerous cases continuously without human interference. This automation technique saved a substantial amount of time and manpower. As the average computation time was around 10 minutes, thus total computation time was around 25 days for all cases.

5. Unsupervised Gaussian mixture model (GMM) clusters

5.1 Introduction to the unsupervised machine learning

Unsupervised machine learning focuses on discovering hidden patterns or intrinsic structures in data without relying on labeled inputs and outputs. Unlike supervised learning, where models are trained on input-output pairs to predict outcomes, unsupervised learning explores relationships in data that are not explicitly annotated. This makes it particularly valuable when labeled data is scarce. Techniques such as clustering, dimensionality reduction, and anomaly detection fall under the umbrella of unsupervised learning. In many real-world scenarios, generating labeled data is resource-intensive, requiring expert input and time. Unsupervised models can autonomously extract meaningful groupings or representations, helping researchers and practitioners make sense of complex datasets. Additionally, unsupervised learning can reveal subtle structures or relationships in data that might otherwise go unnoticed in supervised frameworks[3), 4), 7)].

5.2 Introduction to the Gaussian mixture models (GMMs)

Among the various unsupervised methods, the Gaussian mixture models (GMMs) are well-known probabilistic models used for clustering and density estimation. The GMMs assume that the dataset is generated from a mixture of several Gaussian distributions, each representing a distinct cluster or component. The models estimate both the parameters of these Gaussian distributions (means and covariances) and the probability of each data point belonging to a specific component. The Expectation-Maximization (EM) algorithm is commonly used to iteratively refine these estimates.

GMMs can accommodate clusters of different shapes, sizes, and orientations, making them particularly well-suited for the nuanced patterns often present in structural health monitoring data. Through the use of the Expectation-Maximization (EM) algorithm, GMMs iteratively estimate both the parameters of these distributions and the assignment probabilities of data points to clusters. GMMs are particularly flexible because they can model clusters of various shapes and sizes, unlike simpler clustering methods such as k-means, which assumes spherical clusters of equal size[4), 8)].

When applying clustering techniques such as GMMs, a key challenge is determining the optimal number of clusters or components that best represents the data. Selecting too few clusters may lead to underfitting, missing important structure in the data, while selecting too many can result in overfitting, where the model captures noise instead of meaningful patterns.

The Bayesian Information Criterion (BIC) is a widely used statistical tool to guide this selection process. BIC balances model fit with model complexity by introducing a penalty term for the number of parameters in the model.

When fitting GMMs, the BIC can be computed for models with varying numbers of clusters, and the model yielding the minimum BIC is typically selected as the best compromise between fit and parsimony[9)]. This approach provides an objective, data-driven method for deciding how many clusters are appropriate, without relying on subjective judgment or visual inspection of cluster assignments.

5.3 Application of GMM clusters in damage assessment

The database as described in section 4 was then input into a GMM model to generate the clusters based on the level of damage. The results of the BIC value analysis are shown in **Fig. 6** which shows that the database can be distributed in almost 9 distinctive clusters as there was no ample change in BIC score after that. **Fig. 6** shows the whole dataset in the form of normalized first 3 modal frequencies and then distribution of the database into 9 clusters using GMM clustering approach.

Upon investigating it was found that the data which belongs to either no damage state or cracking only state was allocated to the lowered number clusters i.e. 1 and 2. As the level of damage increased, such as yielding of reinforcement and severe damage, the data allocation was moved to higher numbered clusters. Mean anomaly score

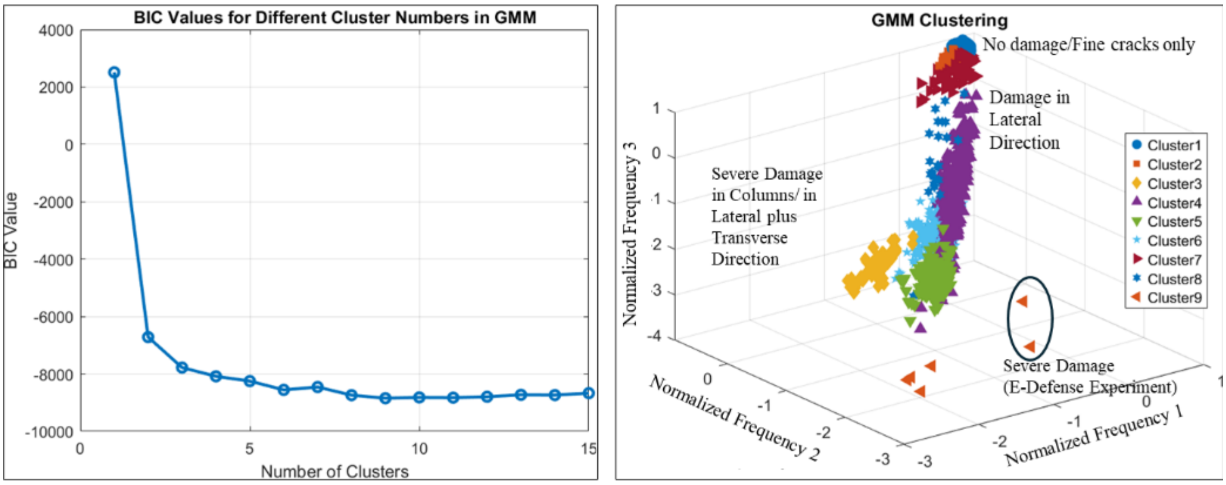


Fig. 6. Selection of number of clusters (Left), GMM clusters for whole dataset (Right)

plot of all clusters is shown in **Fig. 7** which also elaborates the allocation of the data to different clusters.

It was also observed that the clusters that were deviating from vertical axis had damage either in columns or damage in multiple directions.

Furthermore, the experimental data of 2 severe damaged conditions from the E-Defense experiment was also input to the GMM model to verify the accuracy and applicability of the model. It was found the experimental data was allocated to cluster 9 in an unsupervised manner as shown in **Fig. 6** which represents the extreme damage condition. It is worth mentioning that the damage at lower stories was more pronounced as compared to the top story. For example, the same level of damage at the lower story level resulted in a much higher change in modal frequences whereas at the top story the change in modal frequences was much lower. This phenomenon resulted into allocation of datasets from top stories to lower numbered clusters even if the level of damage was higher.

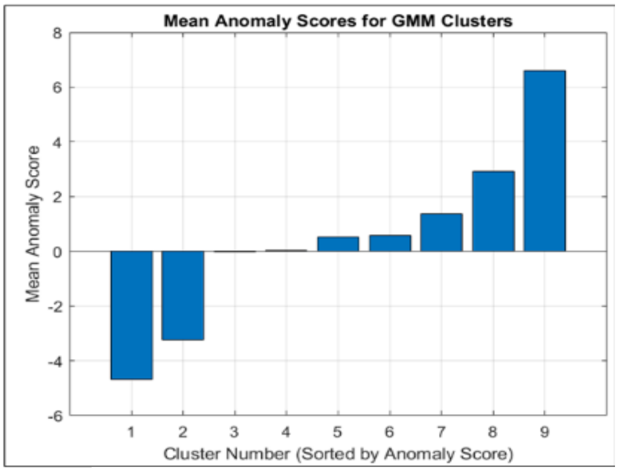


Fig. 7. Mean anomaly score for clusters

6. Conclusions

This paper presented an unsupervised machine learning approach for damage assessment in structures using a large database of modal frequencies. Following conclusions are drawn.

(1) Numerical simulation automation by creating python algorithms proved to be an excellent helping aid to run numerous simulations continuously and creating large database.

(2) The Gaussian mixture model exhibited excellent capabilities of distributing the database of 1st 3 modal frequencies to distinguishable clusters based on damage condition.

(3) It was also possible to observe whether the damage was in one direction or in multiple directions depending on the location of the cluster with respect to the vertical axis.

(4) In case of same level of damage in different stories, the damage was more pronounced at lower story level as compared to top story in terms of change in modal frequencies.

(5) This research exhibited the potential of damage assessment using large datasets, so an extension in the database can result in generalization of this system which may be applicable in all common types of buildings.

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