# Visual Damage Modeling with Physics-informed and Generative Models

Vedhus Hoskere<sup>∗</sup> University of Houston Houston, TX, USA 77204 vhoskere@uh.edu

Subin Varghese University of Houston Houston, TX, USA 77204 srvargh2@cougarnet.uh.edu

Reza Bazrgary University of Houston Houston, TX, USA 77204 rbazrgar@cougarnet.uh.edu

#### Abstract

This paper presents a compilation of three novel methodologies for visual damage modeling of earthquake damaged structures. The methodologies may be categorized as physics-based, unpaired generative, and conditional generative modeling. Physics-based Graphics Models (PBGMs), leveraging traditional finite element with graphics overlays, offer useful visualizations of structural responses under various conditions. Meanwhile, deep learning methods, utilizing structure-specific conditioning signals, can generate novel images reflecting specific damage scenarios very efficiently. We study two conditioning signals, including an undamaged image of a structure and relevant information such as the expected damage state of the member. Together, these methodologies provide promising approaches for visual damage prediction that can be useful for various tasks such as benchmarking of deep learning methods and improving the accuracy and robustness of vision-based systems in assessing earthquake-induced damages via data augmentation.

### 1 Introduction

A visual understanding of the behavior of structural components under extreme loading scenarios, such as earthquakes, blasts, or wind events, is critical for improving design strategies and conducting accurate post-event evaluations. Traditional non-linear analyses, though reliable, are often computationally expensive and time-consuming to produce visually realistic results. The need for efficient tools has led to the exploration of AI-driven approaches that leverage experimental data and curated simulations to train models capable of visualizing and predicting structural responses quickly and accurately. These models enable applications such as design-time visualization, evaluation of critical components such as lateral elements or composite materials, and failure prediction for anchorage systems under diverse conditions. Additionally, they can transform images of damaged structures into actionable parameters for precise assessments and post-disaster recovery efforts.

This paper introduces three methodologies for visual damage modeling of earthquake-damaged structures: (1) physics-based graphics modeling, which combines finite element analysis with graphics overlays for intuitive visualization, (2) unpaired generative modeling, and (3) conditional generative modeling. These approaches provide novel ways to simulate and analyze structural damage, serving as tools for benchmarking deep learning methods and enhancing the accuracy and robustness of vision-based damage assessments. The paper concludes by discussing the implications

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<sup>∗</sup>Corresponding author: vhoskere@uh.edu

and potential applications of these methodologies in improving structural evaluation and design practices.

### 2 Physics-based Graphics Models

[Hoskere et al.](#page-4-0) [\[2022b\]](#page-4-0) proposed a framework for generating physics-based graphics models (PBGMs) as part of a 3D synthetic environment that can support the development of automated inspection strategies for civil infrastructure. The proposed framework involved combining the response of a nonlinear finite element model to inform the realistic graphics-based visual rendering of different damage types. The propsoed framework is illustrated in [1](#page-1-0) and consists of five steps including, (i) graphics mesh, (ii) non-linear finite element analysis, (iii) damage masks generation (iv) damage texture, and (v) scene, lights, camera, and render. The framework was implemented for eleven reinforced concrete building structures subject to earthquake excitation and the damage types rendered included cracks, spalling, and exposed rebar. Images were rendered from the damaged structures, and pixel-level ground truth was automatically generated for the various damage types, for components, component damage states, and depths. As the visual representations are linked to the results of the finite element model, they provide one means of developing vision-based finite element model updating strategies. The framework was implemented to generate the benchmark QuakeCity dataset, a synthetic dataset of damaged buildings with example renderings shown in Figure [2.](#page-2-0) The dataset has since been used in numerous studies [Narazaki et al.](#page-4-1) [\[2023\]](#page-4-1), [Hoskere et al.](#page-4-0) [\[2022b](#page-4-0)[,a\]](#page-4-2) to develop improved semantic segmentation methods and to improve the performance of developed methods on inspection tasks in real images.



<span id="page-1-0"></span>Figure 1: Physics-based Graphics Models Generation Process [Hoskere et al.](#page-4-0) [\[2022b\]](#page-4-0)



Figure 2: Physics-based Graphic Models Rendering Examples [Hoskere et al.](#page-4-0) [\[2022b\]](#page-4-0)

## <span id="page-2-0"></span>3 Unpaired Visual Damage Prediction

[Varghese and Hoskere](#page-5-0) [\[2023\]](#page-5-0) proposed the use of Cycle Consistent Adversarial Networks (CCANs) for image-to-image translation of structural damage. As no existing CCANs produced satisfactory results for damage translation, the paper introduced a new CCAN, termed EIGAN, to translate images between the domains of damaged and undamaged structures. EIGAN incorporated object localization using Eigen-Class Activation Mapping to provide more control over the image translation process and improve performance over existing CCANs. The architecture is illustrated in Figure [3.](#page-2-1)



<span id="page-2-1"></span>Figure 3: Proposed architecture for unpaired damage pattern generation [Varghese and Hoskere](#page-5-0) [\[2023\]](#page-5-0)

EIGAN was able to successfully generate realistic predictions of damage on buildings using undamaged images as input. The authors demonstrated EIGAN's superior performance compared to other established CCANs in terms of data augmentation ability. EIGAN also outperformed existing models on quantitative image evaluation metrics, including Kernel Inception Distance (KID) and Fréchet Inception Distance (FID). Example results are shown in Figure [4.](#page-3-0)

Additionally, the authors introduced an algorithm for latent space exploration for CCANs and implemented it for EIGAN. This algorithm was able to produce smooth translations in the latent space, generating images with varying extents of damage. The generated images can be used to train



Figure 4: Damage prediction using unpaired generative methods [Varghese and Hoskere](#page-5-0) [\[2023\]](#page-5-0)

<span id="page-3-0"></span>robust deep neural networks as part of autonomous condition assessment systems, helping alleviate some of the challenges posed by manual inspections.

# 4 Conditional Damage Prediction

To enable more control over the produced damage patterns compared to unpaired translation, we propose a conditional damage prediction architecture using design parameters. Our network generates specific damage patterns conditioned on the selected features, trained on the results of laboratory experiments in controlled settings. Specifically, we propose and evaluate a conditional diffusion model based on the diffusion transformer [Peebles and Xie](#page-4-3) [\[2023\]](#page-4-3)[,Ronneberger et al.](#page-5-1) [\[2015\]](#page-5-1) to generate crack patterns in concrete shear walls, given the expected damage state of the wall.

A dataset was gathered from the work by [Mansourdehghan et al.](#page-4-4) [\[2022\]](#page-4-4), containing 236 images of reinforced concrete shear walls collected from experimental cyclic loading tests with various drift ratios. Each image in the dataset is has a corresponding set of design features such as geometry, material properties, rebar spacing, and load information. For each image, the set of features is processed through an embedding model fine-tuned to bring image embeddings close to the condition embeddings.



Figure 5: Conditional visual damage modeling using design Parameters

The model is evaluated using 20% of the image set from training. Each image in the validation set is categorized into one of 10 classes with increasing levels of damage. Example results are shown in Figure [6,](#page-4-5) with the first row showing the ground truth from the test set and the second row showing the

prediction. The examples where the prediction and the ground truth are in the same damage category are in green and the exams where there is a difference in damage category are in red.



<span id="page-4-5"></span>Figure 6: Predicted concrete shear wall damage patterns from the proposed model at different damage states

### 5 Conclusions

In this paper, we presented three novel methodologies for visual damage modeling in earthquakedamaged structures: physics-informed image prediction, unpaired damage pattern generation, and conditional damage prediction. Each method offers unique advantages for improving the accuracy and robustness of visual damage prediction systems. Physics-based Graphics Models (PBGMs) provide realistic visualizations grounded in structural behavior, while unpaired translation methods such as EIGAN leverage deep learning to augment datasets and improve predictive accuracy. Conditional models, particularly diffusion-based approaches, enable the generation of highly controlled damage patterns based on specific structural conditions. Together, these techniques present promising avenues for research toward quick extreme event analysis of structural response. Ultimately, improved visual damage prediction can lead to more resilient structural designs and more efficient inspection processes, helping to produce more resilient infrastructure.

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