Generative Adversarial Network for Prediction of Visual Deteriorations and NDE Maps for Bridge Decks

Amirali Najafi¹, John Braley¹, Nenad Gucunski², Ali Maher²
¹Center for Advanced Infrastructure and Transportation, Rutgers University, Piscataway, NJ, United States, 08854
²Department of Civil and Environmental Engineering, Rutgers University, Piscataway, NJ, United States, 08854
Email: amirali.najafi@rutgers.edu

ABSTRACT: Non-destructive evaluation (NDE) techniques are excellent at identifying subsurface deteriorations (e.g., cracks, delamination, and corrosion). NDE surveys of bridge decks are conducted periodically to identify causes and quantify the progress of deterioration. Many transportation authorities however rely on traditional visual assessment techniques for the generation of bridge deck condition indices. The primary limitation of visual assessment is that subsurface conditions and other hidden anomalies are not visible. Many transportation authorities do deploy NDE for condition assessment, however, few techniques are usually used. In this work, a generative deep learning approach is introduced for the two applications: (i) predicting future visual deterioration from past NDE data, and (ii) predicting current conditions map for an unknown NDE technique using a current condition map from a known NDE technique. This approach may be attractive to transportation authorities that may wish to use NDE condition maps to infer future visual deteriorations and other NDE condition maps.

KEYWORDS: NDE; Bridge Deck; Generative Model; Deep Learning; Visual Deterioration.

1 INTRODUCTION

Bridge decks are typically reinforced concrete elements that support and distribute the vehicular loads to the bridge superstructure. Due to exposure to environmental and vehicular loads, and de-icing salts, preserving and repairing bridge decks make up a significant portion of the total bridge maintenance costs [1]. In addition, bridge deck maintenance is both costly and disruptive to highway traffic. Therefore, the Federal Highway Administration (FHWA) instated the National Bridge Inventory (NBI) as a centralized database to monitor and compile information on bridges, including bridge decks. Trained bridge inspectors in all fifty states conduct periodic visual monitoring of the substructure, superstructure, and decks, and generate condition ratings which are then published in the NBI.

The FHWA next emphasized collecting research quality data, including photography, material sampling, and NDE, with the launch of the Long-Term Bridge Performance (LTBP) program. The LTBP program developed a robotic condition assessment tool capable of deploying multiple NDE techniques [2], [3]. A few of the NDE techniques utilized through the LTBP include impact echo (IE), electrical resistivity (ER), ground penetrating radar (GPR), and ultrasonic surface wave (USW). Each of these NDE techniques is used to detect a specific type of deterioration, including reinforcement corrosion, deck delamination, and the overall condition of the deck. The physical and chemical processes causing these deterioration phenomena are often the same or connected [4]. For example, the oxidized product of reinforcement bar corrosion expands, resulting in the formation of microcracks; repeated vehicular loading expands the microcracks into larger cracks, delamination, and eventually spalling.

The current bridge inspection guidelines and the expertise of the bridge inspectors are results of years of experience. Despite the demonstrated potential of NDE methods, an adaption of these technologies will be a gradual process. To narrow the gap between practice and research, this paper aims to develop a predictive model between current NDE-based condition maps and future visual deterioration images. A generative deep learning algorithm approach will be used for this model. The reason for creating such correspondence is that subsurface deteriorations predicted by NDE will eventually surface as visible deterioration with some variability.

Generative Adversarial Network (GAN) are a class of deep learning algorithms that can generate new data from a training dataset and data distribution [5], [6]. A GAN architecture can be implemented for image-to-image mapping [7]. The GAN has two primary components: (i) a generator model which generates synthetic images, and (ii) a discriminator model that labels images as fake (i.e., generated) or real (i.e., from dataset). Simultaneous training of these two models generally results in improvements to both.

In civil engineering literature, GANs have been used for NDE applications [8], [9], shear capacity estimation [10], structural health monitoring and damage detection [11]–[18]. GANs can generate highly realistic images and can model temporal and spatial variations.

In this paper, a conditional GAN architecture is proposed for predictive modeling of visual deterioration and NDE maps. Two applications are studied: (i) prediction of future visual deterioration from a current NDE map, and (ii) prediction of a map corresponding to an unknown NDE technique from a map of a known NDE technique. The second application is attractive in situations where results from one type of NDE technique is available, but results from other needed NDE technique are unavailable. The datasets from the LTBP program are used to synthesize the training data. A heuristic-based approach is used to simulate visual deterioration, due to the limited availability of visual information. Results illustrate that GANs can efficiently predict the deterioration areas and unknown NDE maps.
2 PREDICTIVE MODELING

This section outlines the proposed predictive modeling using a conditional GAN (cGAN) architecture. First, the training dataset is synthesized. For this step, a heuristic-based approach is used to generate synthetic deterioration maps. Next, the proposed architecture of the cGAN is described. Finally, the details of the training and testing procedures are discussed.

2.1 Synthesizing training data

For the two applications discussed in section 1, four NDE techniques from the LTBP dataset are considered: IE, ER, GPR, and USW. Complete photographs of the bridges are unavailable, and only descriptive information about cracking is available. Therefore, highway bridge images from Google Street View were manually unwrapped to form 2D aerial-view images as shown in Fig. 1.

Figure 1. Unwrapping Street View image of a bridge.

The aim of the first application is to predict future deterioration from an existing NDE map. However, long-term visual deterioration such as delamination and spalling are rarely found in the descriptive information provided in the LTBP datasets. In addition, most of the LTBP data were collected in 2-year intervals, which is not enough time for the formation of extensive deterioration. Therefore, synthetic visual deterioration maps need to be generated for the proposed application.

IE is an NDE technique used for the detection of deck delamination and is ideal for guiding the generation of synthetic visual deterioration [19]. The general heuristic-based approach for generating synthetic deterioration maps from IE condition maps is outlined in Fig. 2. The colormap from the IE is used to create masks for cracks and spalls. Spalling is more likely in areas with increased levels of delamination. A Perlin noise algorithm is used to create random crack patterns. Small areas from the spall mask are likely contributors to cracking behavior and hence removed from the spalling mask. To simulate the tapering effect around the edge of spalls, a Gaussian filter is then applied to spall masks to create larger spall areas. A damage mask is created by multiplying crack masks and crack patterns and adding enlarged spall areas. A damage texture is next made by color-coding a 2D Perlin noise. Multiplication of the damage mask and the damage texture results in the deterioration mask. Finally, the deterioration mask can be added to the unwrapped bridge deck images to generate the deterioration map. To avoid distracting the cGAN with lane markers and shadows, the deterioration mask will be used for training in the next section.

2.2 cGAN Architecture

The proposed cGAN is based on the Pix2Pix architecture for image-to-image translation and is illustrated in Fig. 3 [7]. The first half of the generator is an encoder that applies multiple levels of convolutions and max-pooling to downscale an input image into its feature representations. The second half of the generator is a decoder which offers a deconvolution operator and activation functions in multiple levels to generate high resolution imitations of a target image. The skip connections shown with the blue arrows increase the gradient flow through the generator and speed up the convergence during training. The generated and target images are next concatenated and provided to the discriminator model. A patchGAN discriminator is used which works by classifying patches of generated and target image as real or fake, instead of classifying the whole image.

Figure 2. Generating synthetic deterioration map.

Figure 3. cGAN architecture for image-to-image translation.

The total generator loss is comprised of a sigmoid cross-entropy loss between the generated image and an array of ones, summed with the mean-absolute-error (MAE) between generated and target images. The total discriminator loss is calculated as a sigmoid cross-entropy loss between a real image and an array of ones and generated image and an array of zeros. Details for these losses are available in Isola et al. [7].

2.3 cGAN training

The first application considers the correspondence between the current IE condition map and the future visual deterioration of the deck. GPR and ER results are typically influenced by the electrical conductivity of the deck. IE and USW are also both acoustic-based NDEs. Therefore, two possibilities are considered for the second application: (i) prediction of ER maps from GPR maps, and (ii) prediction of USW maps from IE maps.

To increase the size of the training dataset, the NDE condition maps from the LTBP are cropped into squares of 9.1m × 9.1m. A total of 323 image pairs (train: 226, validate:
48, test: 49) are generated for the first application. A total of 260 image pairs (train: 182, validate: 39, test: 39) are generated for each possibility in the second application. In addition, random jittering, mirroring, and cropping are applied to the training dataset.

3 MODELING RESULTS

Each cGAN corresponding to the above models was trained in 200 epochs. The MAE multiplier of $\lambda = 25$ from Isola et al. [7] was used. The Adam optimizing parameters learning rate and $\beta_1$, were selected as 0.0002 and 0.5, respectively. The training was conducted on an NVIDIA RTX 3080 Ti. The total time to train each network was 30 minutes. The setup and training of the cGAN architecture were implemented in Python using Keras, NumPy, Tensorflow, and other standard libraries. Results for the IE to visual deterioration, GPR to ER maps, and IE to USW maps are presented in this section.

3.1 IE to visual deterioration

The cGAN can accurately predict the locations of major spalls. The predicted cracks are random and do not correspond well with the ground truth cracks. This is largely due to the random distribution of the crack patterns. Results for the prediction of visual deterioration from IE condition maps are demonstrated in Fig. 4.

3.2 GPR to ER

The cGAN is able to predict low-frequency trends in ER condition maps. A qualitative comparison between ground truths and predicted ER condition maps in Fig. 5 indicates a good match. Higher-frequency details and noise are not as well predicted.

3.3 IE to USW

The cGAN can predict the general low-frequency trends, however, higher-frequency details are not as well modeled. This is partially attributable to the poor correlation that exists between IE and USW condition maps [4]. The ground truths and predicted USW condition maps are provided in Fig. 6.

3.4 Prediction errors

The errors of the cGAN predictions are presented in terms of MAE. Results from IE to visual deterioration yield the smallest errors. This is due to the deterministic modeling assumptions made when synthesizing training data. Higher errors are calculated for applications of GPR to ER and IE to USW. This is because MAE is emphasizing high-frequency errors. From a qualitative assessment of these results, however, estimated general (low-frequency) trends are well estimated. A summary of the errors is presented in Table 1.

<table>
<thead>
<tr>
<th>Application</th>
<th>Mean MAE</th>
<th>STDEV MAE</th>
</tr>
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<tbody>
<tr>
<td>IE to Visual</td>
<td>0.084</td>
<td>0.026</td>
</tr>
<tr>
<td>GPR to ER</td>
<td>0.502</td>
<td>0.138</td>
</tr>
<tr>
<td>IE to USW</td>
<td>0.455</td>
<td>0.064</td>
</tr>
</tbody>
</table>

Table 1. Application errors.
A deep learning approach was proposed for visual deterioration and NDE condition maps in highway bridge decks. The proposed deep learning algorithm was a cGAN image-to-image translator. The LTBP database and a heuristic-based modeling approach were used to generate training data for the cGAN. Two applications were studied: current NDE to future visual deterioration and known NDE to unknown NDE condition map generation. For the first application, the correspondence of the IE condition map to future visual deterioration was explored. A synthetic visual deterioration database was generated based on a proposed heuristic-based method. For the second application, the GPR to ER and IE to USW correspondences were explored. The cGAN showed excellent potential at modeling the low-frequency relationships between the various datasets. This modeling strategy has great potential, especially as LTBP and other databases grow larger with time and additional field data collections.

REFERENCES


