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Rebar Detection using Ground Penetrating Radar with State-of-the-art Convolutional Neural Networks

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Abstract
Nondestructive Evaluation (NDE) of civil infrastructure has been an active area of research for the past few decades, since traditional inspection of civil infrastructure, mostly relying on visual inspection, is time-consuming, labor-intensive and often provides subjective results. To facilitate this process, different sensors and techniques have been used to effectively carry out this task in an automated fashion. The purpose of this research is to provide a novel learning-based method for detection of steel rebars in reinforced concrete bridge elements. The data from Ground Penetrating Radar (GPR) collected from actual bridges has been used for the development and testing of the novel method. The method utilizes one of the variants of the Convolution Neural Networks (CNNs), namely the Deep Residual Network (ResNet-50). The findings are highlighted through a comparison of the effectiveness in rebar detection with some of the recent works. The results further emphasize the efficacy of Deep Learning-based methods for NDE, both in general and in rebar detection by GPR.

1. Introduction

A modern society's infrastructure comprises mostly of concrete and steel structures, ranging from houses and buildings to transportation infrastructure, such as tunnels, roadways and bridges. The safety of human inhabitants and users is dependent on the regular inspection and evaluation of the civil infrastructure. For the case of transportation infrastructure monitoring, a number of NDE techniques have been explored and implemented in the past. Some of the most commonly used NDE methods include: (i) *impact-echo* (uses mechanically generated vibrations and their reflection to detect sub-surface defects), *active and passive infrared thermography* (provides defect detection using electromagnetic radiations that vary with temperature) and *ground penetrating radar* (the transmission and reception of electromagnetic radio waves to detect underground defects) (Wang et al., 2011; Kee et al., 2012; La et al., 2015; Kaur et al., 2016). Each method has its own set of benefits and limitations.

Traditionally, assessment of civil infrastructures has been performed manually by human inspectors, relying primarily on visual inspection (Wang et al., 2011). However, visual inspection work is time-consuming and prone to errors. Even the NDE methods, like GPR, require extensive effort to manually process raw data and extract relevant information (Dinh et al., 2018). For this reason, an effort is being made towards introducing automation within the process of civil infrastructure assessment by developing new systems, which can facilitate rapid and automated detection and localization of cracks, and other forms of deterioration and defects.

2. Literature Review

In the past, a considerable number of studies have focused towards the development of different techniques for NDE of civil infrastructure. GPR has been used in the assessment of civil infrastructure as far back as the 1970s (Wang et al., 2011). Some of the earlier studies have used GRP data for underground pipe detection (Gamba and Lossani, 2000), as well as detection of various buried objects, e.g., landmines and pipes (Al-Nuaimy et al., 2000). In the case of bridge monitoring, one of the earlier studies utilized GRP data for rebar detection in bridge decks was highlighted by Wang et al. (2011). This particular study made use of partial differential equations and template matching technique with sum of square similarity index for hyperbola localization. One of the studies also proposed the usage of bridge-climbing robot for monitoring the condition of steel bridges (Liu and Liu, 2013). An underwater robotic platform was also developed to monitor the condition of bridge piers, which remain submerged underwater for most of the time (DeVault, 2000). Kaur et al. (2016) developed an automated system for rebar analysis using Histogram of Oriented Gradients (HOG)-based features and Support Vector Machines (SVM). Another research by Spencer and La (2016) proposed a method for rebar detection using Naïve Bayesian classifier trained on HOG features for the detection and classification of GPR-based B-scan images, along with the precise hyperbola localization algorithm for rebar localization. Another recent study by Dinh et al. (2018) proposed a novel method for rebar detection using Convolutional Neural Networks (CNNs).

Apart from the different techniques described in the previous paragraph, a number of different robotic platforms have also been introduced in the prior studies. For example, in the case of bridge evaluation, Gibb et al. (2017) discussed the feasibility of a multi-functional, multi-sensor-based mobile platform for the evaluation and inspection of civil infrastructure. Figure 1(a) highlights the proposed robotic platform. Similarly, Diamanti and Redman (2012) explored the effects of surface and sub-surface layer cracks on the GPR data using a ground-coupled Roadmap system, which has been outlined in figure 1(b). However, the Roadmap platform cannot be considered as a truly robotic platform, as it requires manual assistance in terms of towing and driving with the help of a human driver. Another novel robotic platform, namely the *Robotics Assisted Bridge Inspection Tool* (RABIT) was specifically designed for an efficient automated evaluation of bridge decks (Gucunski et al., 2015, La et al., 2017). *RABIT* has been equipped with state-of-the-art sensor technologies (e.g. impact echo, ultrasonic surface waves, electrical resistivity and GPR), which enable the classification of some of the most common defects in bridge decks, such as

Figure 1: Some of the state-of-the-art robotic platforms employing a wide-range of sensors for infrastructural monitoring (a) NDE robotic platform (Gibb et al., 2017), (b) Roadmap system (Diamanti and Redman, 2012) and (c). RABIT platform (La et al., 2017)

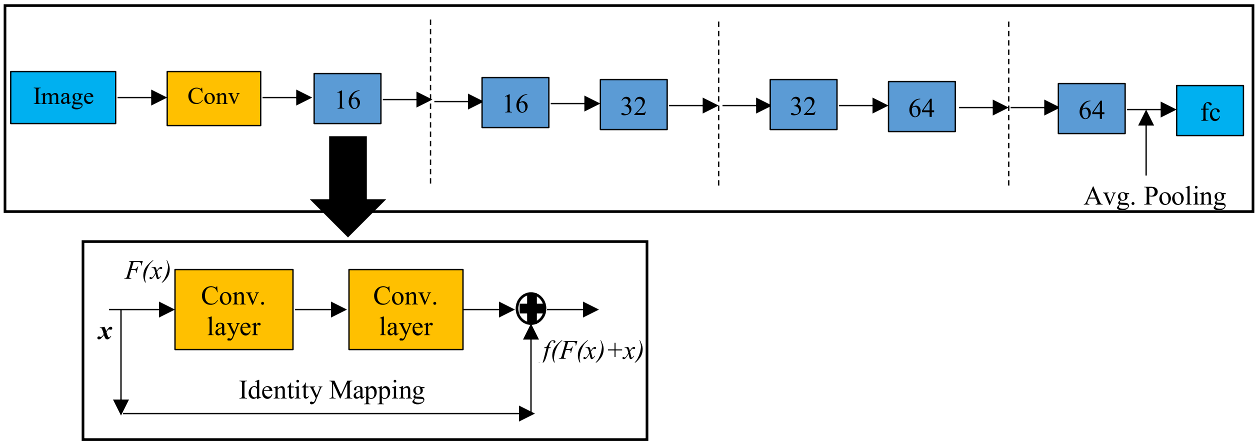

Figure 2: Model depicting the internal structure of ResNet-50

concrete degradation, delamination and rebar corrosion (Gucunski et al., 2015; Kaur et al., 2016). Figure 1(c) provides an instance of the RABIT platform during the actual inspection and evaluation of bridge deck. RABIT provides a wide-array of different functionalities related to the automated monitoring of civil infrastructure using on-surface crack detection and bridge evaluation for signs of deterioration within metal rebar and concrete slabs. The effectiveness of the automated robotic inspection system was also assessed for the evaluation of actual bridges (La et al., 2017).

3. Research Method

In this section, some of the salient features of the proposed technique will be discussed. From a machine learning perspective, the detection and recognition of rebar from other non-rebar anomalies and artefacts detected in B-scans can be considered as a two-class classification problem. Earlier studies have used a number of different methods for rebar detection, ranging from Support Vector Machines (Kaur et al., 2016) and Naïve Bayesian classifier (Spencer and La, 2016) to primitive Neural networks in some of the early studies using GPR (Gamba and Lossani, 2000; Al-Nuaimy et al., 2000). However, the proposed technique of evaluating the effectiveness of Deep Residual Networks (ResNets) towards rebar detection has not been reported in the existing literature. It is for this reason that one of the variants of the Deep Residual Networks, namely ResNet-50 (He et al., 2016), has been employed in this research for the development of rebar detection system. Figure 2 highlights the basic model, which has been used for the development of ResNet-50.

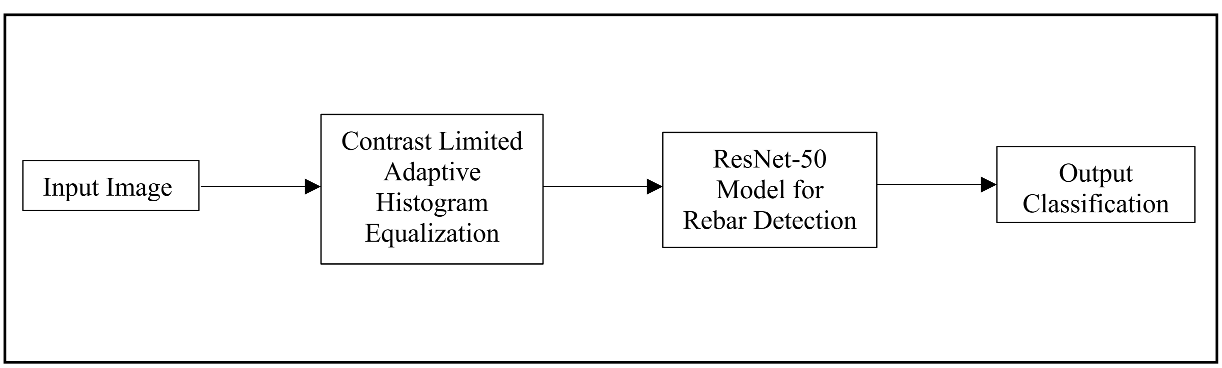

Figure 3: Model of the Rebar Detection System Proposed in this Study

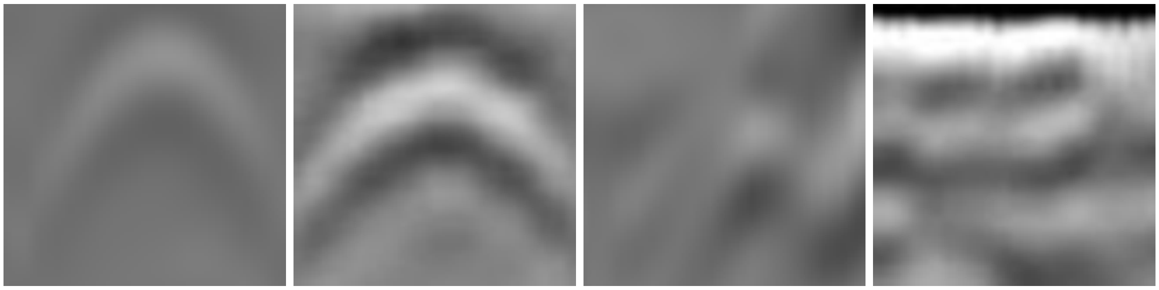

Figure 4: Sample images from the two dataset: (a) positive sample from East Helena Bridge, MT, (b) positive sample from Warren County, NJ, (c) negative sample from East Helena Bridge, MT (d) negative sample from Warren County, NJ

ResNet is one of the recently developed variants of CNN (He et al., 2016), which has gained increased acceptance and popularity in the research community in terms of its widespread application to various computer vision-based problems (e.g. object recognition, image recognition, image segmentation, image super-resolution) (Yuan et al., 2018; Li et al., 2018; Chen et al., 2018). Figure 3 shows the model proposed in this study with Contrast Limited Adaptive Histogram Equalization (CLAHE), which was first proposed in Gibb and La (2016). Unlike Residual Networks, the traditional CNNs suffered from substantial decrease in the overall accuracy as well as increasing error rates with increasing depth of the neural networks (He et al., 2016). Figure 2 outlines the basic building block and structure of ResNet, which can clearly outline the ways in which ResNet differs from its 'plain' CNN-based counterparts, as each residual block (given in the lower part of the figure) skips a few convolutional layers, which enhances its overall optimization and resistance to degradation (Zhang et al., 2018). For the construction of ResNet-50, the block given in figure 2 is replicated multiple times to provide a network with increased depth as well as an overall improved performance. The numbers given on each of the residual blocks correspond to their respective feature sizes. In this study, the system was trained on the existing dataset using learning rate of 10^{-5} to fine-tune the system to the most optimum performance. Depending on the type of dataset being used, the system was trained for a variable number of epochs.

4. Results and Discussion

In this section, the overall performance of the proposed system will be discussed, along with some insights with respect to the dataset that have been used for the training and evaluation of ResNet-50 for rebar detection. Table 1 outlines some of the salient features of the different datasets and the location from which the data was collected. It can be seen from table 1 that the dataset used in this study have been acquired from some of the earlier studies (e.g. dataset for Warren County, NJ from Kaur et al., 2016; dataset from East Helena Bridge, MT from Gibbs and La, 2016), which allow validation of system developed using ResNet-50 by comparing its performance with other relevant studies in the past. Figure 4 shows the sample images utilized from the two dataset.

Table 1: Information regarding different dataset used in this research

		Training		*Validation*	
Location	*Image size*	*Positive*	*Negative*	*Positive*	*Negative*
East Helena Bridge, MT	81 × 81	260	260	40	40
Warren County, NJ	33 × 52	1,200	2,400	300	600
Total	81 × 81	1,460	340	2,660	640

Table 2: Performance of the proposed system using the existing dataset

			Performance	
Dataset	*Image size*	*No. of Epochs*	*Accuracy*	*Error*
East Helena Bridge, MT	81 × 81	24	92.88	0.22
Warren County, NJ	33 × 52	8	98.11	0.06
Total	81 × 81	8	98.47	0.04

Table 2 outlines the performance of the proposed system trained on the different available datasets using some of the most widely employed performance metrics, namely accuracy rate and error rate. The proposed system was trained and evaluated using data from the two datasets individually, which allowed an assessment of different factors affecting the system accuracy. Afterwards, the data was concatenated for the system training using the two datasets in a collective manner. In order to accomplish that, all of the input images were resized to ensure that the system was trained on images with the same size. It can be seen from table 2 that when training for a dataset with limited amount of positive and negative images, there was a need for training the system using a significant number of epochs. However, despite that, the overall error rate was very high (22%), as the overall accuracy of the CNNs and their variants is highly dependent on the quantity of data used for system training. Conversely, when training for a dataset with a reasonable amount of data (e.g. Warren Country, NJ), the system was trained for 8 epochs to reveal very promising results. It can be seen that the system trained using the collective dataset was able to provide an overall accuracy of 98.47%. Table 3 highlights and compares the performance of some of the previous studies in relation to the system proposed in this research. It can be seen that these results are either better than or comparable to some of state-of-the-art systems proposed in the recent past.

5. Conclusion and Future Works

The improvement in automation and accuracy of NDE of civil infrastructure is of paramount importance. Consequently, the research efforts in the future should concentrate on the development of autonomous methods of infrastructure inspection. In order to effectively contribute to state-of-the-art, the work presented in the paper has introduced a novel method for rebar detection using GPR. The results obtained in this research are at par with the performance of recent studies, as shown in table 3. Future studies will attempt to increase the overall size of the dataset used for the system training using ResNet-50. The use of data from multiple bridges will allow the trained system to have high level of robustness to different bridge-level properties (e.g. size of rebar, age of bridge and inherent properties of the different construction materials used).

Table 3: Comparison between accuracy of the different studies for rebar detection

Research	*Accuracy (%)*
Gibb and La (2016)	95.05
Kaur et al. (2016)	98.01[1]
Dinh et al. (2018)	98.75[2]
Ours	**98.47**

1. The highest accuracy result reported in Kaur et al. (2016) has been highlighted here
2. The overall system accuracy given in Dinh et al. (2018) = 99.6% ±0.85%. Therefore, the lower limit of the range was elaborated here

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