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An algorithm for automatic localization and detection of rebars from GPR data of concrete bridge decks

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ABSTRACT

Picking rebars manually in the data from ground penetrating radar (GPR) surveys of concrete bridge decks is time consuming and labor intensive. This paper presents an automated rebar localization and detection algorithm for performing this task. The proposed methodology is based on the integration of conventional image processing techniques and deep convolutional neural networks (CNN). In the first step, the image processing methods, such as the migration, normalized cross correlation and thresholding, are used to localize pixels containing potential rebar peaks. In the second step, windowed images surrounding the potential pixels are first extracted from the raw GPR scans involved in the first step. Those are then classified by a trained CNN. In the process, likely true rebar peaks are recognized and retained, whereas likely false positive detections are discarded. The implementation of the proposed system in the analysis of GPR data for twenty-six bridge decks has shown excellent performance. In all cases, the accuracy of the proposed system has been greater than 95.75%. The overall accuracy for the entire deck library was found to be 99.60% ± 0.85%.

1. Introduction

The use of ground penetrating radar (GPR) in the condition assessment of concrete bridge decks has been well recognized and accepted. This technology provides data of high resolution and quality that can be employed to evaluate various aspects of the deck condition. Specific applications of GPR include evaluation of the deck thickness, localization of rebars in concrete, or measurement of the concrete cover [1]. Furthermore, it can be applied to characterize concrete deterioration, delamination potential, to describe concrete as a corrosive environment, or to estimate the concrete's dielectric constant and conductivity [1–10]. On the other hand, a large amount of data, which the GPR produces, requires extensive manual processing to extract useful pieces of information. Of all the processes, the identification and localization of rebar peaks from B-scans (rebar picking) is well known to be the most labor intensive and time consuming.

Particularly, the manual efforts will be multiplied with the use of multi-channel GPR systems, such as those described in [11]. In such situations, it may take several working days, or even weeks, for a GPR analyst to complete the rebar-picking task for a single bridge deck. Consequently, GPR might not be a cost-effective option and not be considered for deck condition evaluation. In addition, the manual method of picking rebar prevents real-time data processing in the robotics assisted bridge inspection [11]. Motivated by these issues, the main goal of this study was to develop an algorithm that will automate the localization and detection of rebar peaks from GPR data.

Automatic detection of buried objects, in general, and rebars, in particular, in GPR images has attracted much research interest from researchers in different science disciplines. For instance, Al-Nuaimy et al. [12] developed an automatic system that recognizes solid objects, such as pipes and anti-personnel landmines, in GPR images. In the first step of their algorithm, GPR images are segmented using feature extraction and neural networks (NNs) classification. In the second step, the regions classified as target reflections, i.e., reflections from solid objects, are further processed with edge detection and pattern recognition algorithms to identify precise locations of the objects under investigation.

In another study, Gamba and Lossani [13] utilized NNs to investigate hyperbolic signatures of pipes in GPR images. Specifically, a NN detector was developed and applied to find buried objects on GPR images after the images had undergone some pre-processing steps. The purpose of those steps was to enhance the visibility of the signatures of buried objects. Pasolli et al. [14] developed a technique based on a genetic algorithm (GA) to recognize, in binary images, linear and

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hyperbolic signatures of solid, subsurface objects. By using the features extracted from those binary objects, a support vector machine (SVM) classifier was used to categorize them into linear or hyperbolic shapes.

Krause et al. [15] proposed a method that utilizes image segmentation in the detection of rebar objects. Specifically, an image segmentation technique was employed to first isolate arcs in the GPR B-scans. An arc detector was then applied to categorize those based on how well they match a hyperbolic shape. An arc with the highest rating would be regarded as a hyperbolic rebar signature. When the technique was tested on simple GPR scans, the accuracy was reported to be approximately 90%. Such accuracy, however, greatly decreased when the same technique was applied to complicated GPR profiles.

Similar to the detection of pipe signatures mentioned above, a NN was used for the detection of rebars in [16]. Specifically, to identify hyperbolic rebar patterns, the study first used an image processing technique for edge detection. The detected edge lines were then divided into a set of overlapping sections that were used to search hyperbolic patterns using the NN. The technique was demonstrated through a correct localization of two reinforcing bars in a concrete slab. It was, however, evident that the layout of rebars in real concrete decks, and accordingly in real GPR images, is much more complicated than the one used as an illustration in that case study.

In a more recent study [17], a template matching and a hyperbolic curve-fitting algorithm were employed to detect reinforcing steel bars. In the first step, a sum of squared difference (SSD) was utilized to evaluate the similarity between a sliding window of GPR images and a hyperbolic rebar template. When the SSD attained a minimum value, a reference rebar position was selected. Then, with an assumption that the spacing between rebars was fixed, a Fast Fourier Transform (FFT) was used to find the hyperbolic peaks of all the remaining rebars. Finally, a hyperbolic curve fitting was executed to find the parameters of each hyperbola using partial differential equations. There are a few limitations of the approach. The first and biggest limitation is that the template image would need to be selected manually for each bridge deck. The second limitation is the assumption of a fixed rebar spacing, which is not true in many cases. Further limitation is stemming from the fact that the SSD is not a good similarity metric for the template matching for these types of problems. The reason is that, an SSD is affected by the absolute intensity values of the pixels of the two images under comparison. GPR data for different decks, on the other hand, may be collected by different gain setups. Similarly, different rebars in the same deck may be at sections with various degrees of deterioration and, therefore, may have very different amplitudes of reflection.

The methodology proposed in [18] is the most recently presented technique. It uses a SVM classifier to categorize regions in a GPR image into two groups: groups containing, and those not containing rebar signatures. The input of such a classifier is the histogram of oriented gradients (HOG), which is extracted from each windowed image region. After finding likely rebar regions from the SVM classifier, the method uses a hyperbola-fitting algorithm to find rebar peaks in GPR profiles. The proposed methodology was demonstrated in GPR surveys of two real concrete decks with a correct rebar detection of 92.45% and 91.50%, respectively.

2. Research methodology

This study proposes the use of deep convolutional neural networks (CNN) for identification of hyperbolic rebar pattern, after conventional image processing techniques have been employed to localize potential rebar peaks. While the entire process for an automatic rebar picking is summarized in Fig. 1, each of the steps will be described in detail in the subsequent sections.

2.1. Time-zero correction

The setting of zero time position is of high importance for determining correct values of the two-way travel time and, consequently, the rebar depth when processing GPR data. For an air-coupled antenna, the zero time corresponds to the reflection from the ground surface. On the other hand, for a ground-coupled antenna, it corresponds to the direct-coupling reflection. Conventionally, the zero time is placed at either the negative or the positive maximum peaks of the first wavelet. As those peaks do not represent the true time-zero position, the current research employs the zero time as suggested in a previous study [19]. Specifically, the zero time is located at 0.61 ns before the positive peak in the first GPR wavelet. Programmatically, that first positive peak can be searched easily for each GPR signal (A-scan) in a B-scan. After the position of the first positive peak was found for all A-scans, an averaging operation is performed to find the average position of the first positive peak for the entire B-scan. The B-scan will then be corrected for time-zero by discarding all the samples before 0.61 ns of the average position of the first positive peak. A section of a B-scan before and after time-zero correction using the proposed procedure is illustrated in Fig. 2.

2.2. Migration

The purpose of migration is to collapse all hyperbolic patterns associated with reinforcing bars, and to find their true locations. This step should only be done after GPR scans have been corrected for time-zero. A comparison between an original GPR scan, collected by a 1.5-GHz ground-coupled antenna, and the one after migration is provided in Fig. 3a and b. The signal velocity used in the migration was 0.1 m/ns.

A number of different methods for performing migration exist [20]. The hyperbolic summation (HS) migration algorithm was selected for this study. This technique is effective and very easy to understand and, therefore, is most commonly used. Specifically, in the HS algorithm, each pixel with a positive amplitude value in the original GPR image is migrated by guessing all possible locations of reflecting objects. Once this was completed, the amplitude values of pixels at a true object location will end up having the sum amplitude value of all the pixels on the hyperbola. Therefore, in the migrated GPR scans, the energy will be focused on true locations of reflecting objects. On the other hand, the amplitude of a pixel that is not at the apex of a hyperbola will become relatively small compared to those of the pixels at the true rebar location.

In addition, it should be noted that when performing a migration it is very important to select a correct signal velocity. If the velocity selected for the migration operation is lower or higher than the true signal velocity, it will result in “under-migration” or “over-migration”, respectively. Examples of under-migration and over-migration are depicted in Fig. 3c and d, where a signal velocity of 0.07 and 0.13 m/ns were used, respectively. Based on those definitions of migration, and our trial and error experiments for GPR surveys on a large number of concrete bridge decks, a signal velocity of 0.1 m/ns has been selected in this research. That led to correctly-migrated B-scans, as depicted in Fig. 3b. Certainly, one may be concerned with the variation of signal velocity within a single concrete deck, or variations between different decks. As it will be shown later, this assumed velocity worked well for all bridge decks in this study.

2.3. Localization of potential rebar peaks

To clarify the automated rebar-picking algorithm, details of two main steps of the algorithm are described. The first step aims at localizing potential rebar peaks, and is performed on migrated profiles. In the second step, the spatial information of the pixels containing potential rebar peaks in the migrated scans are used to determine the locations of potential rebar peaks in the non-migrated scans. As expected, since the migration operation does not change the size and number of pixels in the GPR scans, the spatial information will be the same for both raw and migrated profiles. Finally, small images