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Review Paper on Crack Detection for Tunnel Inspection using Deep Learning System

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ABSTRACT: Cracks are common defects on surfaces of man-made structures such as pavements, bridges, walls of nuclear power plants, ceilings of tunnels, etc. Timely discovering and repairing of the cracks are of great significance and importance for keeping healthy infrastructures and preventing further damages. Traditionally, the cracking inspection was conducted manually which was labor-intensive, time-consuming and costly. With the development of artificial intelligence (AI), the deep learning technique has achieved great success and has been viewed as the most promising way for crack detection. Based on deep learning, this research has solved four important issues existing in crack-like object detection. First, the noise problem caused by the textured background is solved by using a deep classification network to remove the non-crack region before conducting crack detection. Second, the computational efficiency is highly improved. Third, the crack localization accuracy is improved. Fourth, the proposed model is very stable and can be used to deal with a wide range of crack detection tasks. In addition, this research performs a preliminary study about the future AI system, which provides a concept that has potential to realize fully automatic crack detection without human's intervention.

KEYWORDS:- Cracks, Deep Learning Technique, Tunnel Inspection

I. INTRODUCTION

Tunnel's structural evaluation and maintenance is an important task in civil transportation infrastructures. It is a tedious and resource consuming operation, mainly performed through tunnel-wide visual observations by inspectors; a human has to identify structural defects, evaluate them and then, based on their severity, categorize the liner. Such human-involving approaches have serious drawbacks. On the one hand, as most human-involving approaches, they reduce the operational uptime of tunnels. On the other hand, the empirical evaluation can be often incomplete or not fully reliable due to fatigue, lack of experience, subjectivity, and adverse working conditions. Therefore, significant benefits can be reaped by the adoption of automated speedy inspection and proactive maintenance procedures that would help minimize tunnel closures, while providing accurate structural assessments. Automated methods for visual inspection (VI) based on image processing and machine learning techniques have been applied in various infrastructure monitoring applications cases including roads [1], pavements [2], bridges [3, 4] and sewer pipes[5]. One of the most significant challenges faced by conventional computer vision and machine learning approaches pertains to the need to construct complex handcrafted features (e.g. [6–8]), which will be used to train appropriate classifiers. Therefore, the performance of any approach is affected by the feature space. However, there is a great variety in concrete surface defect types, which makes the construction or selection of effective features a difficult task [9] and often results in bespoke, tailor-made solutions. In recent years, several feature extraction related disadvantages have been mitigated via deep learning approaches. Deep learning models can learn a hierarchy of features by building complex, high-level features from low-level ones, automating the process of feature construction for the problem at hand [10].

Another important factor is computational cost. Many of the existing state of the art techniques that attain good detection rates are characterized by a significant computational burden, which can be put down to both feature extraction as well as the time required by the classifiers employed. Such frameworks are therefore not suitable to make part of a real-world solution for a robotic tunnel inspector. In this work, we present a combinatory deep learning heuristic post-processing scheme in order to identify and classify cracked areas on concrete surfaces for the structural assessment of transportation tunnels. The proposed approach is based on a detection mechanism that operates over the annotations of a convolutional neural network (CNN) on RGB images, acquired by a robotic camera, and a post processing mechanism that eliminates noise related annotations.

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The proposed framework leverages the representational power of the convolutional layers of CNNs, which inherently extract appropriate features, thus obviating the need for the tedious task of handcrafted feature extraction. Additionally, the good performance rates attained by the proposed framework are acquired at a significantly lower execution time compared to other techniques, which makes them a viable real-world solution. In fact, the presented framework has been deployed on a robotic platform and used to drive a real-world automated visual inspection process in Egnatia Motorway in Greece [11].

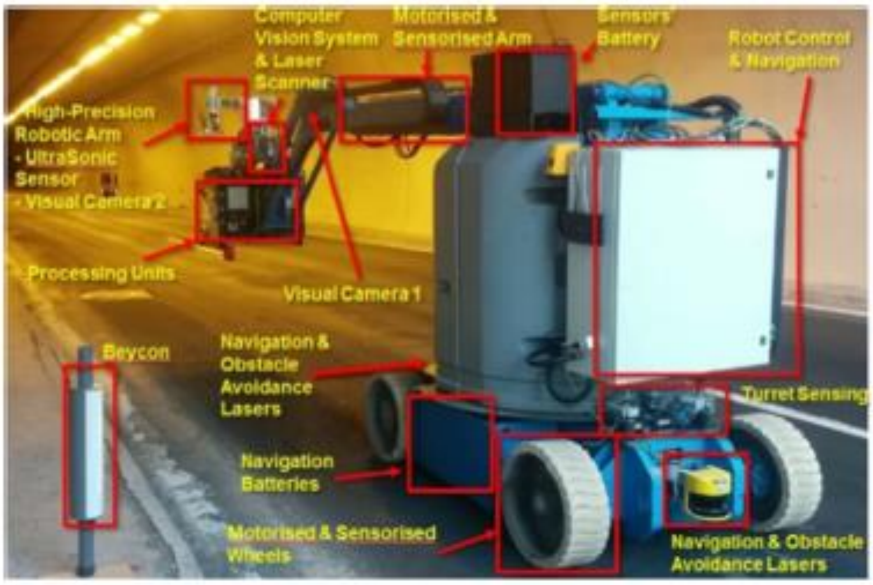

Figure 1: The components of the robo-spect robotic platform

II. LITERATURE REVIEW

The majority of approaches for automated visual inspection including recent ones, rely on the construction of handcrafted features, which are then used as input to classifiers in order to evaluate concrete surfaces and detect defects in infrastructures,including tunnels, bridges, roads, and pavement.

Sariet al. [1],exploits a CNN to hierarchically construct high-level features, describing the defects, and a Multi-Layer Perceptron (MLP) that carries out the defect detection task. Such an approach offers automated feature extraction, adaptability to the defect types, and has no need for special set-up for the image acquisition. Nevertheless, there is a major drawback regarding the applicability in real life scenarios: resources spent for manual data annotation. Data annotation is a time-consuming job that requires a human expert; it is therefore resource-consuming and prone to segmentation errors. For this reason, in some cases semi-supervised approaches have been proposed.

Chen et al. [2],incorporated a prior, image processing, detection mechanism, facilitating the initialization phase. Such mechanism stands as a simple detector and is only used at the beginning of the inspection. Possible defects are annotated and then validated by an expert; after validating few samples, the required training dataset for the deep learning approach has been formed. Finally, a CNN is trained and, then, utilized for the rest of the inspection process. The framework presented in the paper at hand has been deployed on board an integrated, autonomous robotic system for tunnel inspection, which was designed, implemented and validated in the context of the EU ROBO-SPECT project. This fact underscores the contribution of the presented work, since the constraints involved in such a real-world functional system setting make crack detection a far more challenging task compared to, e.g., a standalone desktop application evaluating photographs of concrete tunnel surfaces from a dataset. The most significant of those challenges are: limited processing resources on board the robotic platform; seamless integration with other components of the platform, difficult deployment conditions including illumination and clutter; need for increased detection accuracy at fast response times, since the presented computer vision framework drives the precision positioning of a sensitive

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ultrasound sensor around the crack to further evaluate the defect attributes. Addressing these challenges, along with leveraging a deep learning based computer vision framework with limited training samples, followed by a geometric heuristics-based refinement, while keeping the overall computational cost at reasonable levels, are the main elements of this paper's contribution.

Liet. al. [3],in this paper, a crack detection mechanism for concrete tunnel surfaces is presented. The proposed methodology leverages deep Convolutional Neural Networks and domain-specific heuristic post-processing techniques to address a variety of challenges, including high accuracy requirements, low operational times and limited hardware resources, poor and variable lighting conditions, low textured lining surfaces, scarcity of training data, and abundance of noise. The proposed framework leverages the representational power of the convolutional layers of CNNs, which inherently selects effective features, thus obviating the need for the tedious task of handcrafted feature extraction. Additionally,
the good performance rates attained by the proposed framework are acquired at a significantly lower execution time compared to other techniques. The presented mechanism was designed and developed as a core component of an autonomous robotic inspector deployed and validated in the tunnels of Egnatia Motorway in Metsovo, Greece. The obtained results denote the proposed approach's superiority over a variety of methods and suggest a promising potential as a driver of autonomous concrete-lining tunnel-inspection robots.

Niet al. [4],concrete bridge crack detection is critical to guaranteeing transportation safety. The introduction of deep learning technology makes it possible to automatically and accurately detect cracks in bridges. We proposed an end-to-end crack detection model based on the convolutional neural network (CNN), taking the advantage of atrous convolution, Atrous Spatial Pyramid Pooling (ASPP) module and depthwise separable convolution. The atrous convolution obtains a larger receptive field without reducing the resolution. The ASPP module enables the network to extract multi-scale context information, while the depthwise separable convolution reduces computational complexity. The proposed model achieved a detection accuracy of 96.37% without pre-training. Experiments showed that, compared with traditional classification models, the proposed model has a better performance. Besides, the proposed model can be embedded in any convolutional network as an effective feature extraction structure.

Shenget al. [5],cracks are the most common defect on the surface of tunnels, which potentially brings threaten to the safety of the tunnel and the running vehicles. Timely repairing of the crack is of critical importance. In the past two decades, various vehicle platforms have been developed on the purpose of efficient crack detection and maintenance. With these platforms, images can be captured in a traffic speed, and automatic methods can be developed for fast crack localization. However, for image-based crack detection, traditional methods often meet difficulties in handling cracks with low contrast and poor continuity. In this paper, deep learning based techniques are exploited for feature learning and representation for crack detection. A novel deep neural network is presented for pixel-level crack recognition. Hierarchical features in different stages of the convolution are fused together to overcome the influence of noise and a spatial constraint placed on the target pixels is used to guarantee the crack continuity. In the experiment, a tunnel crack dataset is constructed for performance evaluation.

III. METHODOLOGY

The need to bypass the construction of handcrafted features led to the selection of Convolutional Neural Networks (CNNs) as the core model around which the crack detection mechanism was built, as CNNs use raw image patches as input, which facilitates the classifier implementation. We hereby present the crack detectionapproach deployed.

Crack detection approach

Crack detection given an RGB image is performed in a two-step process, according to a combinatory deep learning heuristic post-processing scheme: i) a CNN based classifier annotates the image and ii) a post processing heuristics-based mechanism is applied on the annotated image to eliminate noise. As a result, the mechanism pinpoints the (x, y) coordinates of a crack position over the image (if any). The steps of the algorithm that detects and pinpoints the crack position are shown in Fig. 2.
Initially, an RGB image pair is captured. The detection mechanism utilizes only one of these two images; the second one is exploited in case of a positive detectionfor 3D reconstruction. Grayscale and resize operators are applied to the image, prior to the assessment by the CNN detector. Both operators, as well as other techniques, were used in order to reduce detection times. Subsequently, the grayscale image is transformed to overlapping window patches of size 13 × 13 pixels. These patches serve as the CNN detector's input. Given the patch, the CNN decides whether the pixel at the

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center corresponds to a cracked area or not. The CNN outputs are then reshaped in order to create a binary annotated image.

Convolutional neural network architecture

The crack detection mechanism revolves around image annotations derived by an appropriately designed and trained CNN. Depending on the application scenario, the main CNN parameters to consider are the filter size, the number of kernels per convolutional layer. The input image patch size and the number of feature maps, as well as the number of neurons in the fully connected layers are of great significance. Given that our work lays emphasis on image segmentation, we need to take into consideration special cases, while at the same time retaining low computational times.

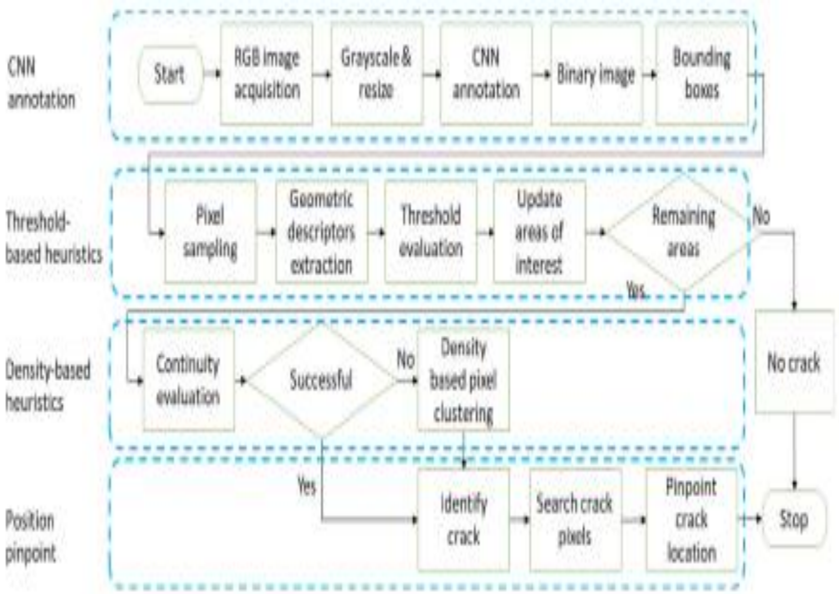

Figure 2: Proposed methodology flowchart

In the case that a CNN is created from scratch (i.e. no pretrained networks are used), training time can span several days on a desktop computer. On the other hand, if we utilize small input patches (e.g. 9 × 9) to reduce structure complexity, the CNN fails to extract appropriately representative features. As such, it cannot generalize well during the inspection of different tunnels. The CNN input comprises patches of dimensions 13 × 13, thus taking into consideration the closest 168 neighbors of each pixel. The designed CNN is depicted in Fig. 3. The first layer of the proposed CNN is a convolutional layer with $C_1 = 19$ trainable filters of dimensions 7 × 7. Since a max pooling layer is not employed, the output of the first convolutional layer is fed directly to the second convolutional layer (40 kernels of size 5 × 5). Subsequently, the third layer (60 kernels of size 3 × 3) creates the input vectors for the Multi-Layer Perceptron (MLP) that follows.

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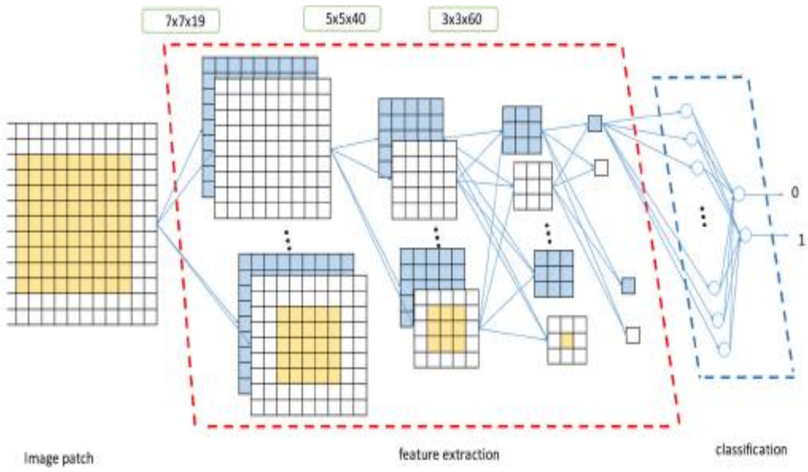

Figure 3:The Architecture of the CNN

IV. EXPECTED OUTCOMES

It is clear that the presented CNN architecture overall outperforms the examined methods in terms of detection performance and computational cost. We now furtherinvestigate the performance of the proposed CNN approach, long with extensions to improve the detection rates attained. Firstly, based on domain expert knowledge, in a practical application if the detection result of a pixel at (x, y) position is positive (i.e. it is a crack according to the CNN), but the actual crack is a few pixels away, the annotation results may still be usable. Therefore, we further evaluated the CNN performance by considering a wider area around the positively annotated pixels. Once the detection is made, we expand the search area within a square bounding box whose side size equals a predefined threshold value. In this case, we only consider images with cracks. Again, CNN inputs were grayscale image patches of size 13 × 13. The output values describe the status of the pixel at the center of the patch (a value of 0 denotes a non-cracked pixel area). As we can see, when considering a slightly more B-flexible threshold of 8 pixels' distance the F1-score increases by 4%.

V. CONCLUSION

An image-based crack detection mechanism for tunnel inspection. The mechanism is based on a deep CNN architecture and post-processing image-based domain heuristics to tackle serious challenges such as the abundance of noise, the need for fast and low-cost computation, poor and variable lighting conditions, low textured lining surfaces, the need to bypass the tedious task of extracting handcrafted features, as well as several operation-related problems and limitations. The presented framework was successfully integrated, deployed and validated in a real-world autonomous robotic inspector used for the visual inspection of a tunnel at Egnatia Motorway in Greece. The obtained results denote that the proposed CNN and heuristics-based approach outperforms existing crack detection techniques offering promising detection rates, at a significantly lower computational cost than compared approaches.

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