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Detection system of inner lining cracks for the Athens Metro

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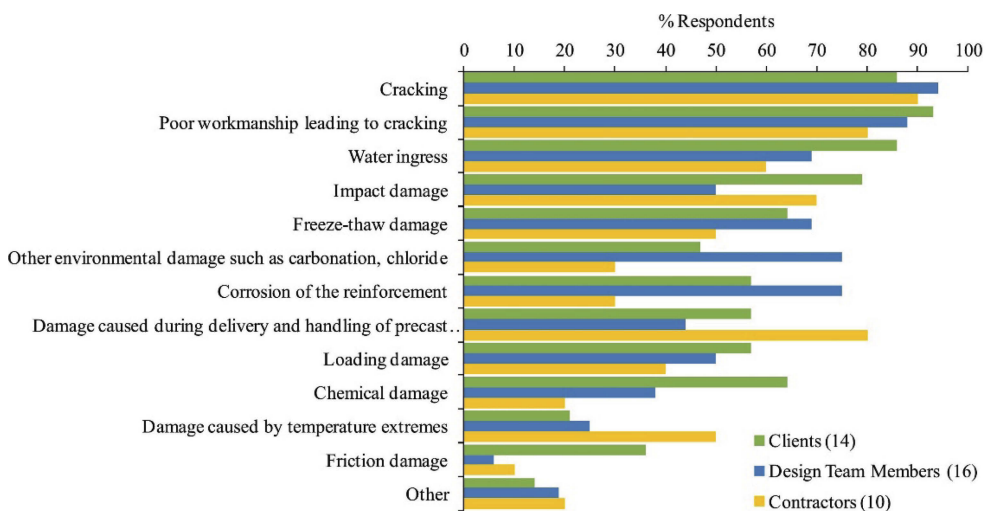
ABSTRACT: A significant aspect of a subway tunnel condition assessment is the systematic inspection of the inner concrete lining state. Fractures and cracks are one of the most common problems of the tunnels in service. It is therefore necessary to detect and classify them according to their characteristics and danger level. Underground infrastructure such as metro tunnels comprise many kilometres in length. Innovative technology is vital for the efficient maintenance through detection of possible failures due to fracturing. We will present a new semi-automatic system of detection of crack presence under development for the Athens metro. The system is composed of an acquisition system (camera) geolocated, a module of cracks detection and an analysis module. In this paper, we will focus on the system core, i.e. segmentation and extraction of the fractures. The segmentation module is based on a class of artificial neural network deemed more suitable for the analysis of visual images, i.e. an efficient convolutional neural network (CNN). So the first step of this study is to find the most suitable CNN and its optimized parameters in terms of precision. Several CNN will be compared. The extraction module will first extract the segmented cracks and then define a set of parameters such as length, width, area and form. This extraction takes into account that the camera has limitations and a crack could be present on several images. Future applications of this system include the automatic surveillance of the fracture evolution in time and the application of adapted prevention measures.

1 INTRODUCTION

Concrete is a material with excellent durability, which explains its wide use as construction material. It is nonetheless subject to material limitations which, in combination to design and construction practices as well as exposure to severe weather conditions can lead to its damage. The damage influences different aspects of the structure, namely the aesthetic, the structural and the functional. Grave factors are those that jeopardise the structural integrity of the structure such as chemical attacks, carbonation, dynamic loading and overloading, dry and wet cycling and fire. The series of CEN standards under EN 1504 define the principles of rehabilitation of damaged concrete structures. The choice of repair materials and systems are also included.

In 2018, a market research exercise was commissioned by the Materials for Life (M4L) EPSRC funded research project. Interestingly, the market research showed (Figure 1) that damage in the form of cracking in concrete structures was experienced

by more clients, design team members and civil engineering contractors than any other problem (Gardner et al. 2018). The predominant strategies for the inspection of concrete structures and the recording of cracks are based on “manual” visual inspection by experienced personnel. It is clear however, that structural tunnel inspection even if performed through scheduled, periodic tunnel-wide visual observations by inspectors who identify defects and rate them, is a slow process with many limitations. The inspectors work in an unpleasant environment of dust, absence of light, uncomfortable conditions and possibly toxic substances. These working conditions are an important motivation to use innovative automated methods for tunnel inspection.



Other includes: Expansion due to ASR. Salt damage. Sulphate damage. Fire damage. Concrete specs have been higher than required which has caused cracking due to brittleness.

Figure 1. Market research results (Gardner et al. 2018 - CC License).

Moreover, the use of innovative technology can provide more objective and efficient maintenance through automatic detection of fractures. It is a task that may be undertaken by an automated system of detection of crack presence. The use of robotic systems in construction is a field with rapid advancements and several studies review their advantages for underground construction. Design of a robotic system includes two main parts, the first being the moving configuration and the second being the set of sensors it will be equipped with, to perform the required detection. The former is generally implemented as a wheeled platform, which has of course limitations in more complex and unstructured environments. There are however solutions such as those reported by Boston Dynamics (Raibert et al., 2008) and their quadruped robot to face a challenging environment, or Unmanned Aerial Vehicles (UAV) to go through uneven terrain.

For the latter, i.e. the sensors part, it is important to notice that the inspection of a tunnel aims at certifying the safety of that structure and that it is also desirable to perform the inspection in a non-destructive way (NDI). Concrete is the most common material in tunnel construction but metal and masonry make up a significant part. Cracks in reinforced concrete due to structural load are frequent. If their width lies within specified limits, usually 0.1-0.3 mm, they are acceptable. The typical defects that are recognizable in concrete tunnels are cracks, spalling and leakage. If the tunnel walls have been covered by a finish such as paint, then their condition is observable on the basis of the deficiencies of the finish. For non-destructive recognition of these features there are several available methods as summarized in Table 1.

Table 1. Non-destructive tunnel inspection methods.

Method	Description
Visual	Well-trained eye
Strength-based	Estimation of surface compressive strength (eg. rebound test)
Sonic	Estimation of strength based on modulus of elasticity calculated from impact-echo sonic pulse travelling speed (e.g. sounding rod)
Ultra-sonic	Estimation of strength based on velocity of pulse generated by a piezoelectric transducer (ultrasonic devices)
Magnetic	Determination of reinforcement position (e.g. Magnetic Flux Leakage method)
Electrical	Determination of permeability and corrosion through measurements of electrical potential differences between reinforcing steel and the surface.
Thermography	Similar to visual method but under infrared radiation. The discontinuities represent barriers to thermal flow.
Radar	Determination of discontinuities based on the propagation of electromagnetic energy (e.g. ground penetrating radar)
Radiography	Determination of density and thickness based on the amount of X or gamma radiation absorbed by structural materials.
Endoscopy	Visual method of unreachable areas based on the insertion of a flexible viewing tube into pre-drilled borehole
Muon tomography	Similar to radiography but based on muon penetration.

Based on the above, a possible configuration for the sensors part would be a combination of visual and ultrasonic systems for crack detection and a 3-D laser scanning system to detect lining deformations. This research does not intend to “reinvent the wheel”, therefore the assumption of a robot composed of at least an acquisition system (camera) geolocated is assumed, a module of cracks detection and an analysis module. This way, our research will focus on the system core, i.e. segmentation and extraction of the fractures and their features.

2 CRACK DETECTION WITH NEURAL NETWORKS

Crack detection using image processing has the advantage of providing more accurate results if compared to the results from conventional manual methods. Digital cameras currently have at least 12 megapixels image resolution, which enables the detailed acquisition of concrete surface by using simply a mobile phone. Early methods for crack recognition typically applied threshold-based approaches to find the region of cracks. The basis of that approach was that crack pixels must be darker than surrounding pixels and brightness was the feature taken into consideration (Li & Liu, 2008). Obviously, these methods are overly sensitive to noise and lacking in global view of the forming crack (Shi et al., 2016). The suppression of noise is mostly countered by incorporating more features such as gray-level value based on various methods such as the Otsu (1979) threshold selection method (Nhat-Duc, 2018) or the method of Kapur et al. (1985), or the neighboring difference histogram method proposed in Li & Liu (2008). Apart from the pixel-based analysis of images, block-based crack detection is also reported in literature (Oliveira & Correia, 2013). State-of-the-art crack detection methods include CrackTree (Zou et al., 2012), CrackIT (Oliveira & Correia, 2013), FFA (Nguyen et al., 2011) and MPS (Amhaz et al., 2014).

2.1 Convolutional neural networks

In the last decade, deep convolutional neural networks (DCNN) have been developed for image classification and general object detection thanks to the developments in computing power and the large amounts of data supplemented by improved algorithms and large tagged

datasets such as ImageNet (Deng et al., 2009). A Convolutional Neural Network (CNN) is a multi-layer Artificial Neural Network designed especially to handle two-dimensional input data. Convolutional neural networks (CNNs) have more hidden layers and complex network structure than traditional machine learning methods.

The idea behind a convolution is to study how a function acting on another function brings out a modified one. It is performed by doing element-wise multiplication between a kernel, i.e. a mask, and each sub-matrix of the original image matrix and sum the result into a single integer or floating value. Then, a transformed or filtered matrix is obtained and converted back into an image. If the original image was a gray-scale image, each pixel contains values between 0 and 255 which makes the computation easier compared to a color image with [RGB] triplets stored in each pixel. The kernel may be a function like the famous edge detection Canny (1986) algorithm, or one that sharpens or increases contrast between bright and dark regions of the image. The concept of convolution is depicted in Figure 1 where the upper left 2x2 part of an image is converted to a matrix and then convoluted to a reduced matrix 1x1. A simple convolution neural network model structure diagram is shown in Figure 2. It includes two convolution layers C_1 and C_2 and two sub-sampling layers S_1 and S_2 . First the image is convoluted by a 3-kernel filter and three feature maps are obtained in the S_1 layer. Then, the procedure is repeated with C_2 and S_2 layers, and the final output is vectorized and input into the traditional neural network.

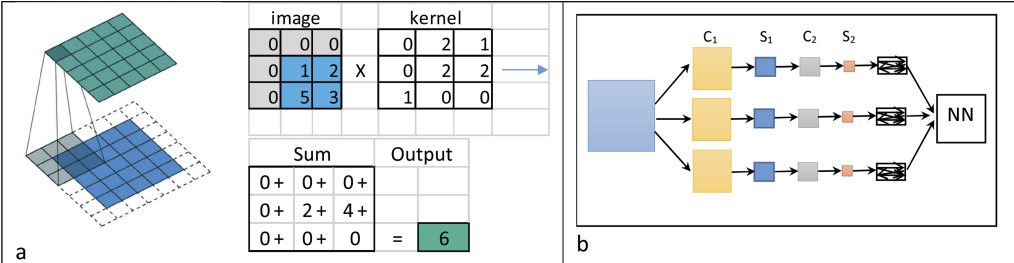


Figure 2. (a) Concept of convolution, (b) Simple CNN structure.

In a crack detection sequence, after the image acquisition, a series of actions are performed in a linear fashion, in order to obtain the final estimation. A diagram of crack detection sequence is depicted in Figure 3. In that sequence, the CNN concerns the stage of image processing and the NN the stage of image segmentation. Pre-processing involves mainly the correction of luminosity with the purpose to ease the cracking detection process by both reducing noise and enhancing the dark linear features. Post-processing concerns the re-assembling of the image parts.

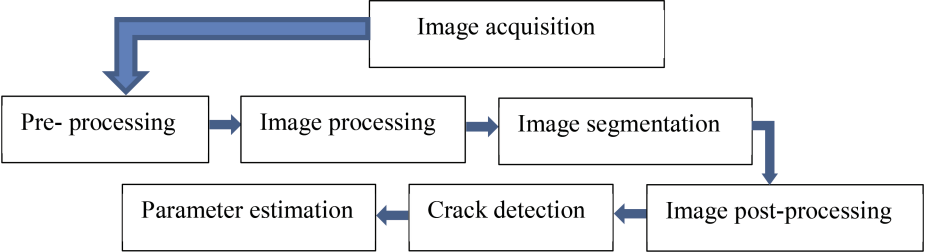


Figure 3. Diagram of actions sequence for crack detection based on image acquisition.

Many CNN structures have been developed for the image processing of pavement, building, bridges and road fractures. Dais (2020) has tested numerous CNNs on masonry walls of historical buildings. They considered VGG16 (Liu et al., 2015), MobileNet (Howard et al., 2017),

MobileNetV2 (Sandler et al., 2018), InceptionV3 (Szegedy et al., 2016), DenseNet121 and DenseNet169 (Huang et al., 2017), ResNet34 and ResNet50 (He et al., 2016) as well as DeepLabv3+ (Chen et al., 2018), DeepCrack (Liu et al., 2019), and FCN based on VGG16 (Liu et al., 2017). These networks were used in the frame of transfer learning and gave a score F1 between 79.6% and 75.4%. Yang, 2019 used pyramidal networks on road cracks. They compared five types, namely HED (Xie & Tu, 2015), RCF (Liu et al., 2017), FCN (Long et al., 2015), CrackForest (Shi et al., 2016) and their own FPHBN.

2.2 Selection of CNN

The first important selection for this research was the selection of NN type for image segmentation. As presented in the previous paragraph the literature presents numerous possibilities. Further, the KERAS library contains about forty models that can be tested.

In our research, five CNNs were selected for testing that belong to three types of architecture, namely U-Net, Fully Convolutional Network (FCN) and Feature Pyramid Network (FPN). U-Net and U-Net reduced, FPN, Linknet and DeepCrack in transfer learning mode. The basic architecture of U-Net can be found in Keras library documentation. It consists of two symmetric paths, one contractive and one expansive, thus forming a U shape, hence its name.

2.3 Training of the CNN with crack images

It is important to train the selected CNNs with one or more suitable image databases available. The objective is to be able to perform fast and accurate segmentation of images containing cracks. The task requires the training of the NN with a maximum number of images representing different situations. Five different databases were selected for this purpose:

2.3.1 Crack_detection_CNN_masonry (Dais, 2020)

This is database of 241 color images of 224x224 size in png format and 241 segmentation images (masks) of the same size and format.

2.3.2 Crack500 (Yang et al., 2019)

This is a database of a total 587 png format images and masks in 640x360 sizes.

2.3.3 Deepcrack (Liu et al., 2019)

This is a public benchmark dataset with cracks in multiple scales and scenes to evaluate the crack detection systems. All of the crack images are manually annotated.

2.3.4 Crack forest dataset master (Shi et al., 2016)

This is an annotated road crack image database. It contains 157 images 320x420 and their segmentation.

2.3.5 Data Maguire 20180517 (SDNET2018)

This is a database of 230 images originating from bridge decks, walls and pavements cracks. Each image is segmented into 256×256 px sub-images labeled as C if there was crack or U if there was not. The final database contains 18K sub-images.

3 SEMI-AUTOMATIC INSPECTION OF TUNNEL IN ATHENS METRO

The Athens Metro construction began in 1992 from the Larissa Station. The first milestones in the construction progress include the arrival of the TBM at Syntagma Square in 1997 and the completion of the track laying related works for SYNTAGMA – SEPOLIA and SYNTAGMA – ETHNIKI AMYNA sections and first partial opening of the System in 2000.

The implementation of new network extensions has continued and Line 4 is currently underway. The newer lines are expected to be in an excellent state, the older ones however, are entering an era of more demanding inspection and maintenance. It has been decided to focus on the older construction parts of the Metro so as to be sure to include cracks in our images.

3.1 *Access, programming and timing of the inspection*

The timing of inspections and the state of the structure are correlated. The environmental conditions should be recorded as a routine part of any inspection. The current and recently prevailing conditions are important, e.g. the efficiency of the drainage system will be more apparent in wet periods and cracks may be more open in cold weather. The existing access opportunities should also be taken into consideration. For the case of a railway track, the tunnel would be some distance from the access point. For the case of avoiding disruption to other activities, inspection may be planned to coincide with other maintenance, repair or monitoring work. A touching distance inspection is required. Tunnel inspection for the Athens Metro, is currently performed by the personnel of the former Athens-Piraeus Railway Company STASY S.A. It takes place between 1.00 a.m. and 4.00 a.m. when there is no public using the rail. The crack inspection focuses on water presence, as mentioned earlier and it is performed in combination to other maintenance tasks.

3.2 *Crack repair strategies*

There are currently two main courses of action for the Athens Metro and they both fall under the hand-placed polymer modified cementitious materials.

3.2.1 *Dry superficial cracks*

Superficial crack repairs are carried out by sealing the surface of the crack to prevent the ingress of moisture and deterioration of the adjacent materials. These capillary type cracks and their surrounding area showing no sign of moisture are thoroughly cleaned with water or pressurized air from cement deposits, dust, soil, oils, grease, etc. Then, temporary surface sealing along the crack by a suitable material (epoxy paste, polyester putty, etc.) is followed by drilling holes directly in the crack and placing special nozzles (packers) for the introduction of the grout. The number, diameter, position and depth of the holes depend on the characteristics of the crack (length, width, depth). After the temporary crack seal has cured, the crack is filled by epoxy resin by pressure injection in successive layers, through the packers, starting from the lowest nozzle in vertical cracks or one edge in horizontal cracks until completely sealed.

3.2.2 *Superficial cracks with water flux*

These are leaking capillary type cracks that occur in structural concrete where there is no waterproofing system in accordance with specifications. After the intervention, the now dry cracks are sealed, according to the previous case. The concrete surface to be repaired is again thoroughly cleaned. For cracks that show tear-like leaks without pressure, a temporary surface seal along the crack with a suitable material such as fast setting hydraulic cement, is applied with a view to immediately stop the leak. If the cracks show leaks with high water pressures, polyurethane foam is first injected to temporarily seal the crack. Holes are drilled for grout injection on either side of the crack at an angle of 45° at sufficient distances from and between the crack and of suitable depth so that the holes penetrate the crack interface. Permanent sealing of the crack is effected by applying a suitable material (acrylic, polyurethane, or epoxy resin suitable for leaking cracks), injected under pressure through the packers. The material has adequate fluidity to be able to penetrate and cover all the voids and pores of the concrete ensuring the complete filling of the crack.

3.3 Image acquisition

The station at Katehaki was selected for image acquisition for several reasons. It is a section of the Athens Metro that was constructed in 1995 and that is currently closely monitored and with newer geotechnical investigations and studies due to new line extensions. Further, the area combines two out of three types of construction used, namely Cut & Cover and Segmental Lining with TBM, while the one missing is the Conventional Excavation that has been used in other areas of the network with more complex geotechnical profiles such as the tunnel that connects Syntagma to Monastiraki Station. The concrete used was C20/25, reinforced with steel S500 while the reinforcement cover was 60mm. The vertical (main) reinforcement bars were $\Phi 25$ while the horizontal $\Phi 20/20$ mm. Three samples of the images taken are depicted in Figure 5.

3.4 Segmentation of crack images

The images were cut up in patches of 224x224 px with an overlap of 112 and then segmented by use of a NN. At the end of the procedure, the images were re-combined. The patch size was selected in order to fit all the CNNs selected to be used.

4 RESULTS

In this section, the performance of the five models is compared and summarized. The following metrics are used: Accuracy = $(TP+TN)/M$; Precision = $TP/(TP+FP)$; Recall = $TP/(TP+FN)$; F1-Score = $2 \cdot (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$, where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives and M is the number of samples.

4.1 Validation results from the trained CNN

All selected CNNs were trained with 80% and validated with 20% of the available datasets. Figure 4 contains indicative results from the training graded on their F1 score and Tables 2 and 3 all related metrics.

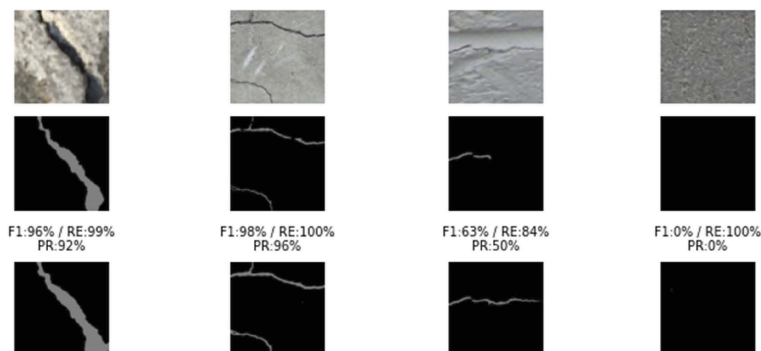


Figure 4. Results from the trained CNN.

Indicative results from the trained and validated CNNs for the Athens metro photographs are contained in Figure 5. In the case of fine cracks in continuous concrete structure and uniform illumination the results are satisfactory. However, in section of construction with pre-fabricated concrete segments and in the presence of efflorescence, more training is required.

Table 2. Train evaluation indexes.

	epoch	F1_score	F1_score_dil	Precision	Precision_dil	Recall	accuracy	loss
unet reduit	101	0.873	0.981	0.783	0.973	0.990	0.990	0.072
unet	78	0.892	0.991	0.813	0.989	0.993	0.991	0.034
fpn	112	0.765	0.951	0.645	0.942	0.963	0.977	-0.074
linknet	57	0.710	0.833	0.587	0.763	0.948	0.969	0.168
deepcrack	119	0.972	0.999	0.947	1.000	0.999	0.998	0.008

Table 3. Validation results.

	F1_score	F1_score_dil	Precision	Precision_dil	Recall	accuracy	loss
unet reduit	0.774	0.838	0.788	0.926	0.778	0.982	0.536
unet	0.853	0.939	0.804	0.967	0.918	0.988	0.201
fpn	0.712	0.824	0.720	0.971	0.735	0.976	0.091
linknet	0.736	0.824	0.657	0.802	0.880	0.974	0.230
deepcrack	0.874	0.926	0.855	0.959	0.901	0.990	0.284

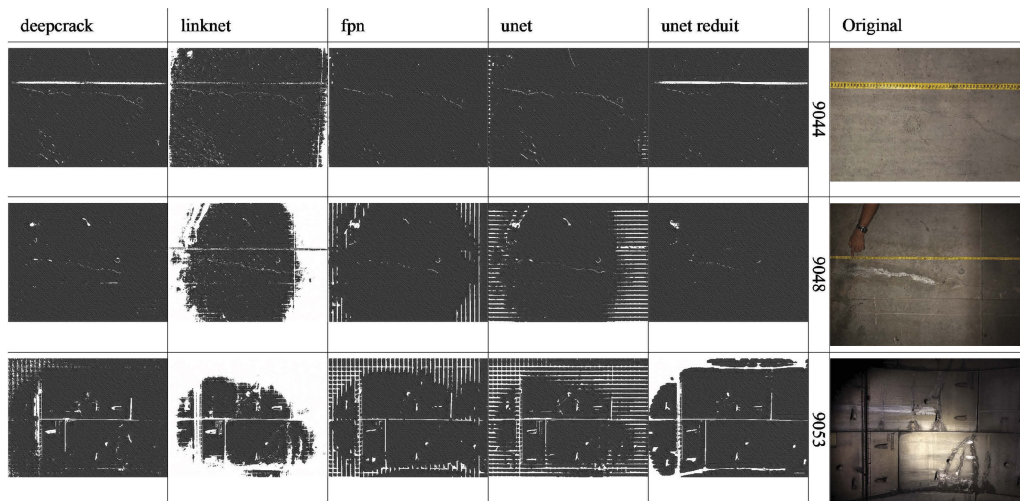


Figure 5. Indicative results from the Athens Metro crack pictures.

5 CONCLUSIONS

The first main stages for the rehabilitation of damaged concrete structures are currently performed by skilled personnel and include registration of the state of the structure and determination of the causes of damage. Optical recognition of common defects in tunnels includes cracks in various patterns, spalling, pop-outs, efflorescence, staining, delamination, honey-comb and leakage.

The advances in neural networks and image segmentation have provided tools for the automation of maintenance in concrete underground structures. In the case of the Athens metro, the implementation of these techniques by use of U-Net/reduit, FPN, LinkNet and Deep-Crack has shown great potential. It has also been shown that further training of advanced CNNs is generally required to cover for specific factors such as type of construction, illumination and environment.

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