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Literature Survey on Road Crack Detection

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A B S T R A C T

The crucial task of automatic crack detection has the potential to drastically reduce the manual, labor-intensive building and road inspections that are currently carried out. The accuracy of detection has been significantly improved by recent research in this area. However, the approaches frequently rely heavily on expensive annotation processes. Additionally, new batches of annotations are typically required for each new environment in order to handle a wide range of target domains. Because of this, when crack detection systems are actually put into use, the cost of data annotation becomes a significant obstacle. We propose a two-branched framework and formulate the crack detection problem as a weakly supervised problem to address this issue. Our framework is less affected by annotation quality because it combines predictions based on pixel brightness with those of a supervised model trained on low-quality annotations. Even with low-quality annotations, the proposed framework maintains its high detection accuracy, as demonstrated by the results of the experiments.

Keywords: Supervised-learning, image-recognition, road crack, aigle , CNN.

1. Introduction to Road Crack Detection.

1.1 Introduction

The significance of break location is perpetually featured by the new fast development in the quantity of old streets and structures. As it is difficult to distinguish crack patterns from complex surface textures, the majority of studies naturally focus on increasing detection accuracy .Consequently, recent studies demonstrate high detection rates for a variety of datasets, at least in situations where the train and test domains match. As a result, we believe that other facets of crack detection should receive greater attention. The cost of annotating the collected data is one of the biggest barriers to real-world deployment of crack detection systems. Pixel-level supervision, one of the most expensive annotations to acquire, is required because the crack detection problem is formulated as a semantic segmentation problem. Sadly, it is also difficult to train a robust crack detector that can be used in any situation because the definition of a crack varies from site to site and crack patterns vary greatly between materials. For instance, if the walls at Site B are constructed of stone tiles and naturally contain black line patterns, a straight, black line on a wall that is considered to be a crack at Site A will not be considered to be a crack at Site Being order to maintain high detection accuracy across all sites, new annotation sets must be created for each site in order to train site-specific detectors, which adds to the annotation burden.

We have decided to concentrate on lowering the annotation cost while maintaining accuracy because we are aware of this issue. To this end, our contributions are summarized as follows:

i. The crack detection problem is formulated as a task with weak supervision, and we provide two manual annotations and a set of synthetic annotations for this new task.

ii. A framework that we propose might serve as a solid foundation for the task. A straightforward component that can be incorporated into any semantic segmentation network to improve performance under weakly supervised conditions is the focus of our proposal.

iii. Through extensive experiments on four network architectures and three datasets, we demonstrate that the proposed framework works well in settings with low levels of supervision.

1.2 Motivation

i. Due to our increasing use of the space environment for satellites, GPS navigation, television, and cell phone communication, space weather research studies the interactions of the solar terrestrial environment.

1.3 Aim and Objective of the work

i. Automatic crack detection is a critical task that has the potential to drastically reduce labor-intensive building and road inspections currently being done manually.

ii. The project sought to use a convolutional neural network (CNN) to produce an app which can identify and classify road damage.

iii. Visual signs of cracks and depressions indicate stress and wear and tear over time, leading to failure/collapse if these cracks are located at critical locations, such as in load-bearing joints.

2. Scope of ML in Crack Detection

Applications of machine learning and statistical techniques have increased across a variety of fields in recent years as a result of the explosion in computing power and available data. The scientific process, from data analysis to modeling, has benefited from the application of these techniques in astronomy and space sciences. For the purpose of forecasting solar flares, a variety of machine learning and statistical techniques are currently being utilized, allowing for early warning of severe flares.

2.1 Specifications

i. Weakly, Semi, and Unsupervised Anomaly Detection.

ii. Macro Branch Models.

iii. Low Quality Annotation.

iv. Class Rebalance Weight Sensitivity.

v. Agile, CFD, DCD models.

vi. F1 score Based analysis.

2.2 Equations

i. *F1 Score* = $\frac{2TP}{2TP+FP+FN}$

ii. Algorithm 1:

Annotation Synthesis Pipeline

Input : P // Set of Precise Annotations n dil

// Number of dilation to apply

Output: S // Set of Synthesized Annotations

1 S ← ∅ // Initialize S to be empty

2 for all p ∈ P do

3 αL ← 10

4 αU ← 10000

5 repeat n dil times

6 d ← Dilate(p)

7 repeat

8 Sample random integer α between [αL, αU]

9 s ← Elastic Transform(α, d)

10 r ← Recall(s, p) // Calculate recall \

11 if r ≥ αU then

12 αL ← α

13 if r ≤ αL then

$\alpha U \leftarrow \alpha$

until $0.925 \leq r \leq 0.975$

$S \leftarrow s$ // Append to S

return S

2.3 Features

i. Learning Based Approach

To fine-tune the inner parameters of the model, these methods make use of data samples. One of the most studied methods in this category is based on deep learning. The work of Zhang et al., for instance, where prediction was made with a shallow CNN, and Fan et al.'s work, which introduces the concept of structured prediction to force the model to learn the relationship between adjacent pixels. Inoue and co. Proposed the Multiple Instance Learning architecture (MIL) to improve the network's rotational robustness. MIL is similar to test time augmentation but is also used during training time. To better combine information from multiple scales, other works employ deeper CNNs with an encoder-decoder architecture and skip connections.

ii. Anomaly Detection: Weakly, Semi-, and Unsupervised:

As stated in Section The annotation cost is one of the biggest roadblocks to deploying a crack detection system. We look at three common methods for lowering the cost of annotation in this section. The first strategy is to make the problem a weakly supervised one and lower the quality of the annotations. It is possible to annotate samples more quickly and in a shorter amount of time by lowering the quality of the annotation. Fan et al., for instance their model with annotations at the image level, which only indicate the existence of a crack in an image but do not provide precise location information. The fact that the supervised model can only isolate crack regions up to rectangular patches is one major drawback of their proposal. The post-processing rule-based method must be extremely accurate because these selected patches mostly contain non-crack regions due to thin cracks, as mentioned in Section. I-A. The second strategy involves annotating a few samples and presenting the issue as a semi-supervised one. Self-training, in which thresholder prediction values serve as the ground truth for unlabeled samples, is one common method of semi-supervised learning. Using agreement among ensembled models and the high entropy nature of anomaly samples are two other methods. The final approach formulates the problem as an unsupervised problem and completely eliminates the requirement for annotation. The rule-based methods mentioned in Section are examples of this approach. I-A. Machine learning-based techniques like auto-encoders and generative adversarial networks have recently emerged. Models learn to reconstruct undetected images using these techniques. The model's inability to accurately reconstruct deficient images allows for crack detection.

2.4 Illustrations

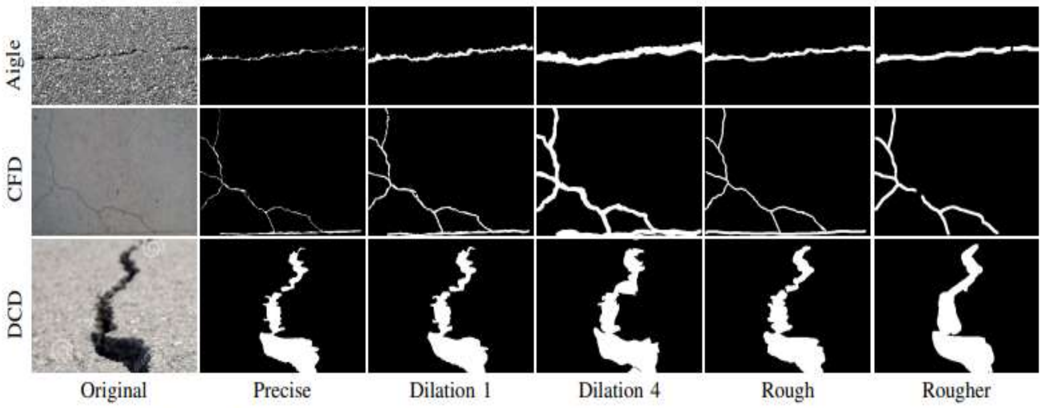
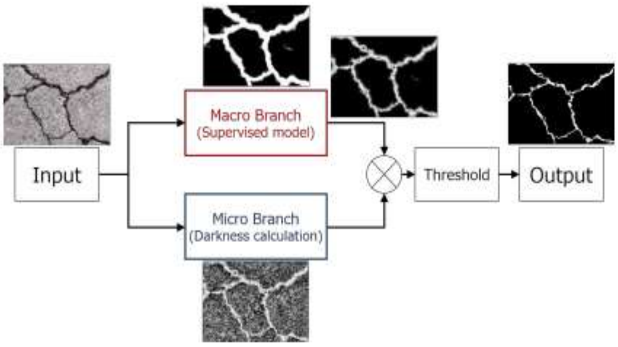


Fig. 2: Annotation samples (white pixels: crack regions, black pixels: non-crack regions).

	Train Dataset												
	Inoue Light			Inoue			DeepCrack			DeepLab V3+			MiB only
Test Dataset	Aigle	CFD	DCD	Aigle	CFD	DCD	Aigle	CFD	DCD	Aigle	CFD	DCD	
Aigle	**0.477**	0.461	0.405	**0.725**	0.509	0.501	**0.724**	0.534	0.571	**0.616**	0.281	0.444	0.473
CFD	0.571	**0.587**	0.525	0.638	**0.678**	0.603	0.637	**0.657**	0.566	0.583	**0.667**	0.556	0.377
DCD	0.659	0.674	**0.782**	0.764	0.727	**0.795**	0.548	0.330	**0.841**	0.819	0.669	**0.842**	0.728



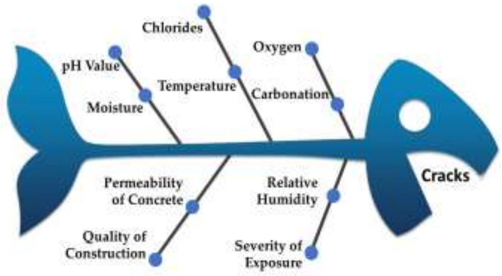
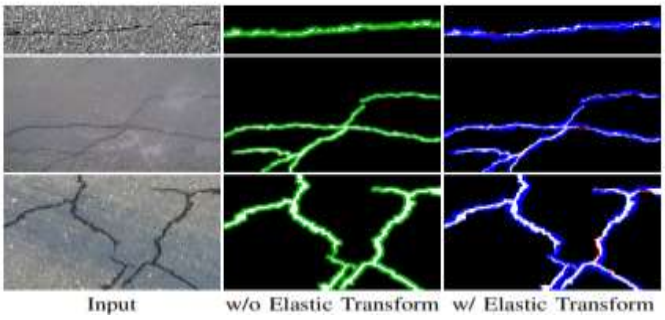


Figure 1. Possible causes of cracks in concrete structures.



2.5 Methodology

i. Annotation Reduction Strategy

There are three ways to cut down on the cost of annotation: weakly, semi, and unsupervised methods. For the following reasons, the crack detection problem will be formulated as a weakly supervised problem in this paper.

There are two options for us as a result. Because precise annotation takes significantly less time than approximate annotation, the weakly supervised approach was chosen over the semi-supervised approach. This is due to the fact that determining the location of crack boundaries consumes the majority of annotation time, as crack and non-crack regions frequently have ambiguous boundaries. Additionally, the complexity of boundary lines makes annotation of the boundaries time-consuming. The annotators are able to ignore both of these issues with approximate annotation. Crack detection was formulated as a weakly supervised problem as a result.

TABLE I: Dataset information and annotation times (in hours). *Indicates that only train images are annotated.

Dataset	Sample counts		Annotation times (hr.)		
	Train	Test	Precise	Rough	Rougher
Aigle	24	14	-	0.45	0.3
CFD	71	47	21.5	2.3	0.72
DCD	300	237	-	8.1*	1.45*

TABLE II: Training parameters of the tested models. Inoue Light model shares the same parameters as Inoue *et al.*

Model	lr	# epochs	w_c^{model}	Notes
Inoue *et al.*	1e-1	50	20	lr halved every 20 epochs
DeepCrack	1e-3	700	33.3	lr decayed after 400 epochs
DeepLab v3+	5e-3	200000	100	Xception 65 backbone [22], PASCAL VOC pretrained

ii. Two Branched Approach

Figuring out break location as a pitifully managed problem implies that the comment names contain botches, for the most part around the break limits. As a result, the boundary information that was lost during the annotation process must be recoverable by a crack detector. In order to accomplish this, we looked at how human annotators mark cracks and discovered that the annotation procedure typically consists of two steps. First, an annotator examines the entire image to determine the approximate locations of cracks. The annotator then zooms in on a section, contrasts the darkness of its pixels with those of its neighbors, and labels the dark pixels as cracks.

2.6 Enhancement

In this paper, we propose a method for locating drivable road areas in monocular images. The road detection algorithm can be trained using this self-supervised approach without the need for any human road annotations on the images. Training can be scaled up and labeling by humans is made easier with our method. We consolidate the best of both administered and unaided strategies in our methodology. In the first place, we consequently produce preparing street comments for pictures utilizing OpenStreetMap1, vehicle present assessment sensors, and camera boundaries. Using these annotations, we train a Convolutional Neural Network (CNN) for road detection. We show that we can create sensibly precise preparation comments in KITTI informational collection. Among the methods that do not necessitate the effort of a human annotation, we achieve the most advanced performance.

3. Conclusion

As the world's roads and buildings continue to grow, automated inspection is becoming increasingly important. However, in order to maintain their high accuracy, the current crack detectors require a significant number of expensive annotations at each site. In order to reduce the annotation bottleneck, we investigated the weakly-supervised approach to the crack detection problem and proposed a framework that can maintain high performance even when only low-quality annotations are available. A straightforward unsupervised component based on pixel brightness is included in our framework and can be incorporated into any semantic segmentation network to improve its capacity to learn from low-quality data.

We demonstrated that our framework is not only simple to implement but also highly effective in weakly supervised settings through extensive experiments on four distinct model architectures trained with manually and synthetically generated low quality annotations from three distinct datasets. This makes it an appealing addition to existing crack detectors.

We would like to look into different configurations for the proposed branches in the future, as well as broaden the Micro Branch so that it can be used for other semantic segmentation tasks.

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