



Crack Detection as a Weakly-Supervised Problem: Towards Achieving Less Annotation-Intensive Crack Detectors

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Crack Detection

- HITACHI Inspire the Next
- There are many roads and buildings desperately in need of maintenance
- Can we automate the inspection process to cut cost?
- Crack detection problem is formulated as a semantic segmentation problem
 - Pixel-level output provides other information necessary for inspection, such as crack width and orientation





- For real life deployment, prediction accuracy is not enough
 Annotation process is a huge bottleneck
 - 1. Pixel-level annotation
 - 2. Difficult to make robust crack detectors, because cracks can form on any surface in many different shapes

...quick search for "crack" on the internet



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Crack Detection as Weakly-Supervised Problem

- We propose a weakly-supervised approach to crack detection problem
- It is much easier to approximately annotate cracks
 - ✓ 9-30 times faster!
- Rough annotation = rough prediction...



Input

Precise annotation

Rough annotation

ΗΙΤΔ(:ΗΙ



Method

Macro Branch

 Regular supervised crack detector, predicts using global information

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Micro Branch

Rule-based detector, predicts using localized information





Experiments

Low Quality Annotations

- Need low quality annotations to evaluate under weaklysupervised settings
- Prepared synthetic and manual annotations for evaluation
- Synthetic annotation pipeline
 - 1. Apply dilation operation to the precise GT
 - 2. Distort the result using Elastic Transform
 - Distortion is applied until the generated annotation achieves recall value between 0.925 and 0.975



Sample Outputs

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[4] Yuki Inoue and Hiroto Nagayoshi. Deployment conscious automatic surface crack detection. In WACV, pages 686–694. IEEE, 2019.
[5] Yahui Liu, Jian Yao, Xiaohu Lu, Renping Xie, and Li Li. Deepcrack: A deep hierarchical feature learning architecture for crack segmentation. Neurocomputing, 338:139–153, 2019.

[6] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In ECCV, 2018.

Sample Outputs





Micro Branch cleans the

[4] Yuki Inoue and Hiroto Nagayoshi. Deployn
[5] Yahui Liu, Jian Yao, Xiaohu Lu, Renping X Neurocomputing, 338:139–153, 2019.

rough output

ges 686–694. IEEE, 2019. chitecture for crack segmentation.

[6] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In ECCV, 2018. © Hitachi, Ltd. 2021. All rights reserved. 9



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Results on Manual Dataset





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End

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Prediction across different datasets



Out-of-domain vs. weakly-supervised results.

Bold indicates the best results for the setting.

		In	oue Lig	ht		Inoue						
	Aigle	CFD	DCD	R	R-er	Aigle	CFD	DCD	R	R-er		
Aigle	-	0.645	0.475	0.773	0.781	-	0.669	0.654	0.816	0.802		
CFD	0.607	-	0.542	0.621	0.591	0.647	-	0.625	0.631	0.597		
DCD	0.721	0.760	-	0.824	0.811	0.795	0.785	-	0.836	0.813		

	DeepCrack						DeepLab V3+						
	Aigle	CFD	DCD		R	R-er		Aigle	CFD	DCD		R	R-er
Aigle	-	0.748	0.694		0.816	0.808		-	0.278	0.498		0.773	0.811
CFD	0.635	-	0.548	(0.629	0.590		0.590	-	0.573		0.641	0.599
DCD	0.565	0.382	-		0.835	0.830		0.829	0.686	-		0.842	0.823