#22-Spatial-temporal motion field analysis for pixel-wise crack detection on concrete surfaces

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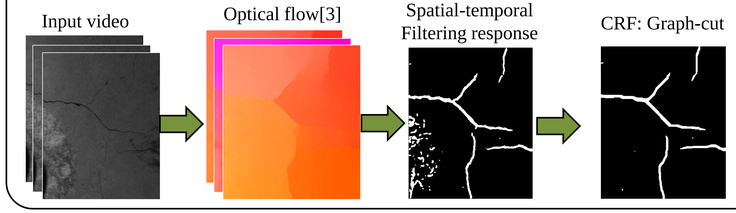
Overview

Issue: Detection of early-stage micro-cracks are difficult by image intensity based methods since micro-cracks have poor visibility.

Solution: Use pixel level frame-wise motion discontinuity to find cracks.

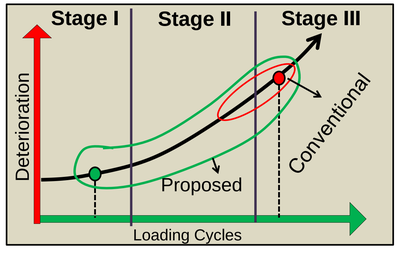
Key Contributions

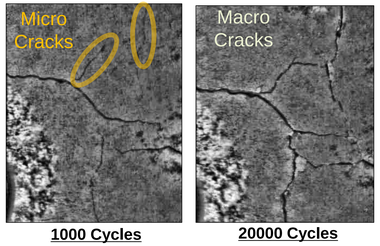
- Spatial-temporal motion field discontinuity based early-stage crack detector.
- Structured output by graph-cut inference on CRF for high precision detection.



Crack propagation

- Crack propagation occurs in three stages : (1) fault initiation, (2) growth and (3) accelerated growth. Most image intensity based detectors are in stage 2 and 3.
- Early stage crack detection is important to ensure safety by predicting the growth of cracks in future. Additionally, it is cheap to perform repairs at early stage.





1000 Cycles 20000 Cycles

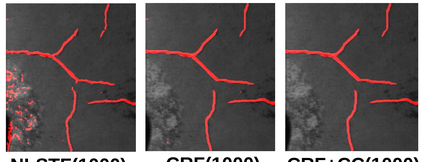
- Traditional methods fail to accurately detect early stage crack because of poor clarity. Hence, we propose to use a spatial-temporal motion features.

Problem formulation as CRF

- Frame the crack detection problem as a pixel-wise binary classification problem given the dense 2D motion in every frame computed using optical flow.

Given $\boldsymbol{X}$, the stacked motion vectors, find binary matrix $\boldsymbol{Y}$ that maximizes the MAP distribution.

$$\hat{\boldsymbol{y}} = \arg\max_{\boldsymbol{y}} \; P(\boldsymbol{Y}=\boldsymbol{y}|\boldsymbol{X}) = \arg\max_{\boldsymbol{y}} \frac{1}{Z(\boldsymbol{X})}\exp(-E(\boldsymbol{y}|\boldsymbol{X}))$$



NLSTF(1000) CRF(1000) CRF+CC(1000)

Minimize the energy,

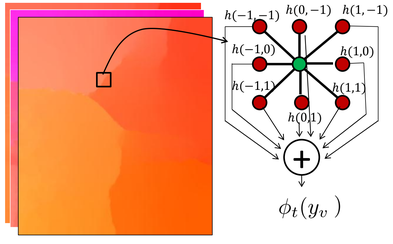
$$E(\boldsymbol{y}) = \underbrace{\sum_{v\in\boldsymbol{V}} \phi_t(y_v)}_{\text{Data term}} + \underbrace{\sum_{(u,v)\in\boldsymbol{E}} \phi_p(y_u, y_v)}_{\text{Smoothness term}}$$

Use graph-cut inference - heuristic data and smoothness terms.

Data and smoothness terms

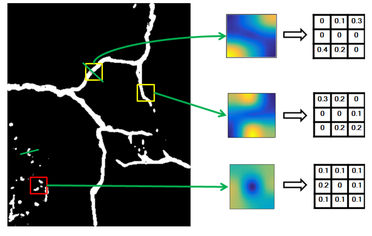
Data term (NLSTF)

Find distance in temporal motion vectors

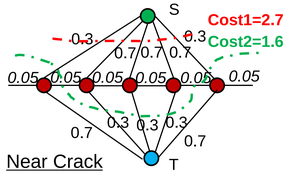


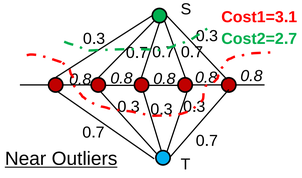
Smoothness term

Find local orientation using HOG[4]



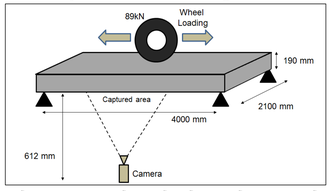
Min-cut illustration





Experimental results

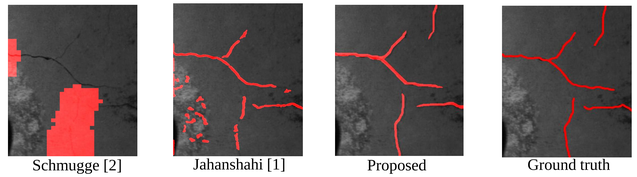
- Experiment consists of small bridge specimen with cyclic wheel loading.



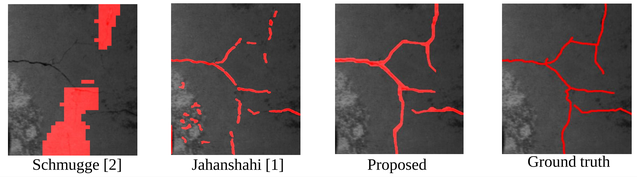
- Qualitative and quantitative evaluation shows that proposed method can detect early stage cracks (high TPR at 1000 cycles) and has less false positive detections(low FPR overall).

Method	1000 Cycles			5000 Cycles			20000 Cycles		
	TPR	FPR	F1	TPR	FPR	F1	TPR	FPR	F1
Schmugge [2]	0.37	0.15	0.32	0.48	0.12	0.46	0.84	0.31	0.49
Jahanshahi [1]	0.78	0.12	0.61	0.80	0.08	0.73	0.92	0.09	0.76
Proposed (NLSTF)	0.83	0.16	0.62	0.91	0.09	0.80	0.93	0.06	0.85
Proposed (CRF)	0.85	0.05	0.80	0.95	0.05	0.87	0.93	0.04	0.89
Proposed (CRF+CC)	**0.85**	**0.04**	**0.83**	**0.95**	**0.03**	**0.92**	**0.93**	**0.03**	**0.90**

1000 cycles



5000 cycles



References

[1] M. R. Jahanshahi, S. F. Masri, C. W. Padgett, and G. S. Sukhatme. An innovative methodology for detection and quantification of cracks through incorporation of depth perception. *Machine vision and applications*, 2013

[2] S. J. Schmugge, L. Rice, N. R. Nguyen, J. Lindberg,R. Grizzi, C. Joffe, and M. C. Shin. Detection of cracks in nuclear power plant using spatial-temporal grouping of local patches. WACV, 2016.

[3] C. Liu, W. T. Freeman, and E. H. Adelson. *Beyond pixels: exploring new representations and applications for motion analysis*. PhD thesis, MIT,2009.

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