Multi-Scale Deep Pixel Distribution Learning for Concrete Crack Detection

Xuanyi Wu, Jianfei Ma, Yu Sun, Chenqiu Zhao, Anup Basu

Dept. of Computing Science, University of Alberta, Canada

Overview of State-of-the-art

- Vision-based Crack Detection Methods:
  - Using local patterns
    - Basic feature extractor

      i.e. Gabor filters, HOG, and LBP
    - Sobel and gradient-based operators

      discuss edge detection techniques in the frequency domain
  - Using both local patterns and a global view
    - i.e. Cracktree

Overview of State-of-the-art

- Deep Learning-based Crack Detection Methods:
  - Crack detection based on some existing networks
    - i.e. Feature Pyramid and Hierarchical Boosting Network (FPHBN)
  - Crack detection and crack segmentation at the same time
    - i.e. Deep Convolutional Neural Network and Adaptive Thresholding

Summary of approach

- **Step1 : generate Random Permutation of Spatial pixels (RPoSP features).**

- Denote the given concrete image as I(x, y),where x and y is the location of pixels. Mathematically we can calculate the RPoSP feature extracted from the pixel located at(x, y)

$$\mathrm{RPoSP}_{x,y}\,(m, n : R_i, R_o) = I(x, y) - I(x + r(m), y + r(n))$$
$$m, n \in [1, R_i]\,, \quad r(m), r(n) \in [1, R_o]$$

Note:

m,n: the indices of an entry in a patch.

r(): the random permutation step.

Ri and Ro are the parameters to control the size of RPoSP features under multiple scales.

Summary of approach

- **Step2 : Feed the groups of patches into a CNN.**

Instead of feeding the whole images, we only feed groups of patches into a CNN

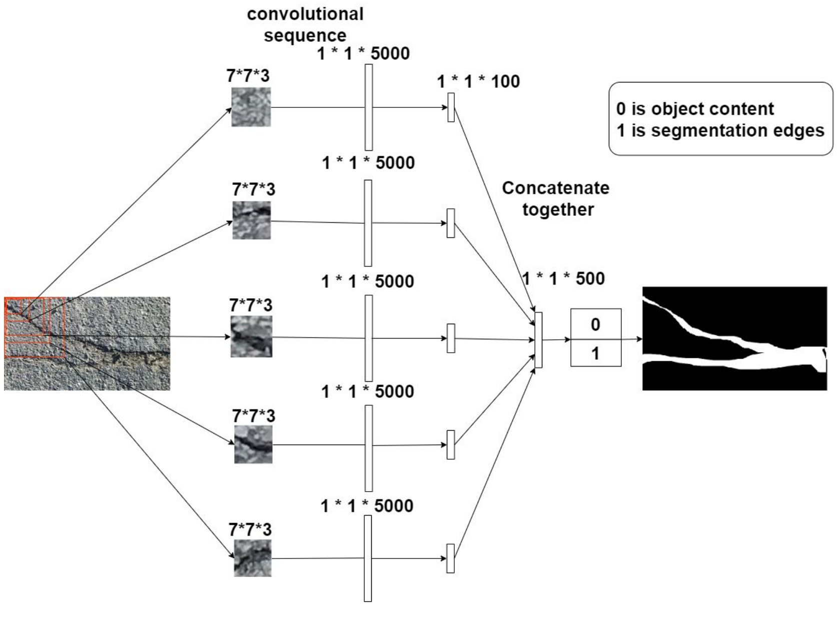


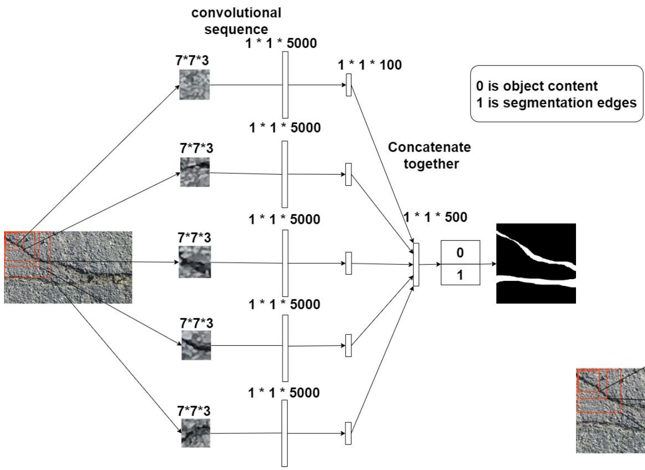
Figure: MS-DPDL Net 1

Patches with different scales go into different convolutional sequences as shown in the figure.

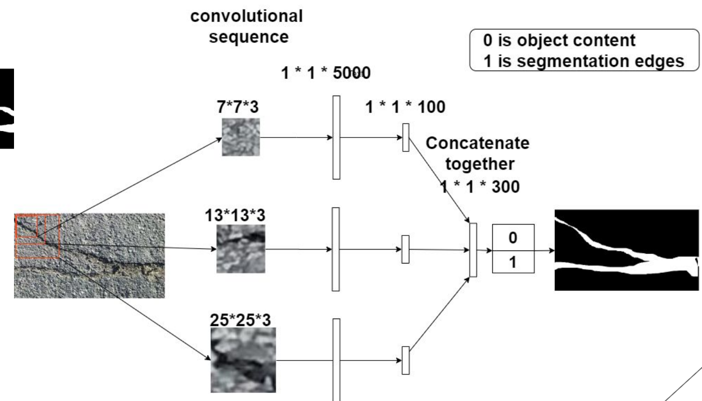
The output is the predicted label (0 or 1) for the central pixel in the input patch

Summary of approach

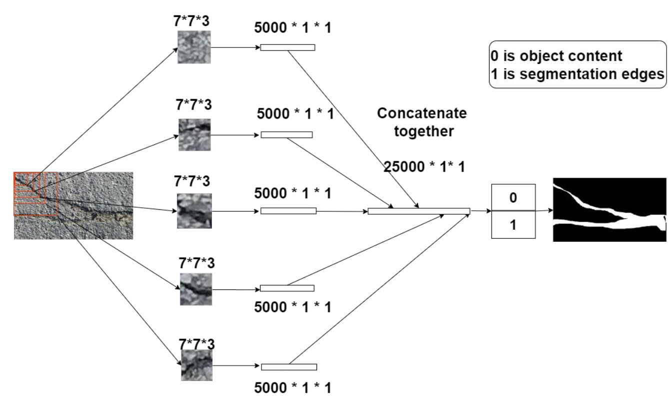
- **3 Networks we used in this paper.**



MS-DPDL Net 1



MS-DPDL Net 2



MS-DPDL Net 3

Experimental Details

- Dataset CRACK500

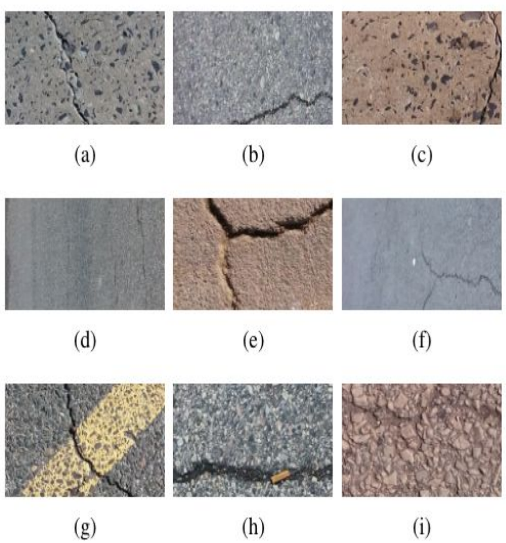


Figure: Examples of cropped images in CRACK500

- Concrete Crack Images for Classification

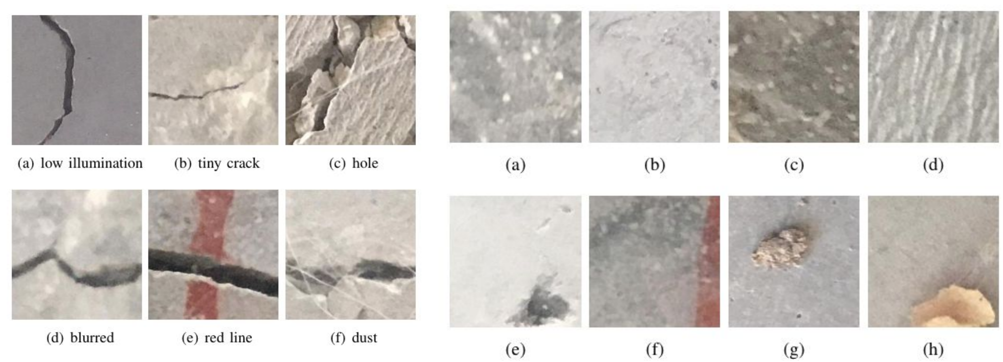
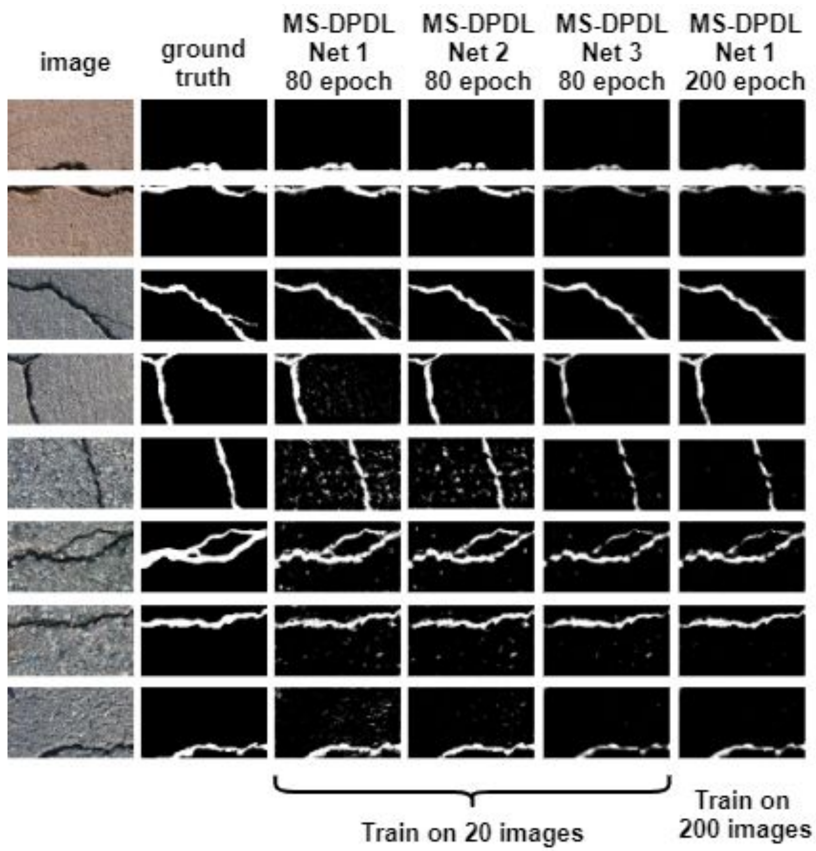
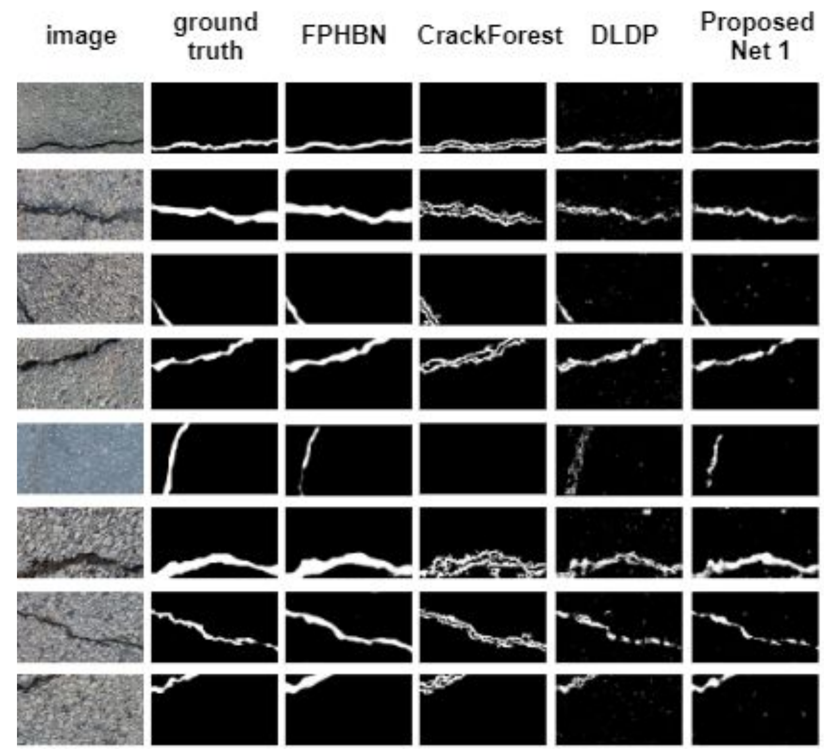


Figure: Examples of cracked and non-cracked images

Comparisons

Qualitative Comparison for segmentation





Comparison

Quantitative Comparison for classification:

The pre-trained MS-DPDL Net 1 model (80 epoch) is used directly to test on another dataset *Concrete Crack Images for Classification*.

TABLE II
A QUANTITATIVE COMPARISON OF DIFFERENCE MODELS' CLASSIFICATION PERFORMANCE.

Measurements	Recall	Precision	Fm	Accuracy
Proposed MS-DPDL	**0.9916**	**0.9918**	**0.9916**	**0.9920**
CNN(Sitara) [21]	0.94	0.95	0.94	0.99
VGG16 [21]	0.92	0.93	0.92	0.96
VGG19 [21]	0.73	0.80	0.76	0.81
Inception ResNet [21]	0.93	0.93	0.93	0.98
SVM [22] [23]	0.7333	0.6875	0.7096	0.7187
CNN [22] [24]	0.7802	0.8875	0.8304	0.8187
FCN(Manjurul) [22]	0.941	0.913	0.927	0.928
CNN-AT(Rui) [16]	0.9992	0.9992	0.9992	0.9992

TABLE III
DPDL RESULT ON 40K IMAGES, K=3650

Measurements	crack	non-crack	overall
Re	NA	NA	0.60980
Pr	NA	NA	0.60577
Fm	NA	NA	0.60778
Accuracy	0.6098	0.60315	0.606475

TABLE IV
PROPOSED MS-DPDL RESULT ON 40K IMAGES, K = 40.

Measurements	crack	non-crack	overall
Re	NA	NA	0.9733
Pr	NA	NA	0.97711
Fm	NA	NA	0.97520
Accuracy	**0.9733**	**0.9772**	**0.97525**

Conclusion

- Three different MS-DPDL network implementations show similar results on limited training data, which shows the strong learning ability for the multi-scale structure.

- The outstanding performance on a totally new dataset demonstrates the good transferability of the proposed model.

Conclusion

Future work:

The patch generation and permutation steps need to be repeated millions of times. We plan to develop a more efficient algorithm to reduce the time complexity for training.

Thank you

Questions ?