Multi-illumination Fusion with Crack Enhancement using Cycle-Consistent Losses

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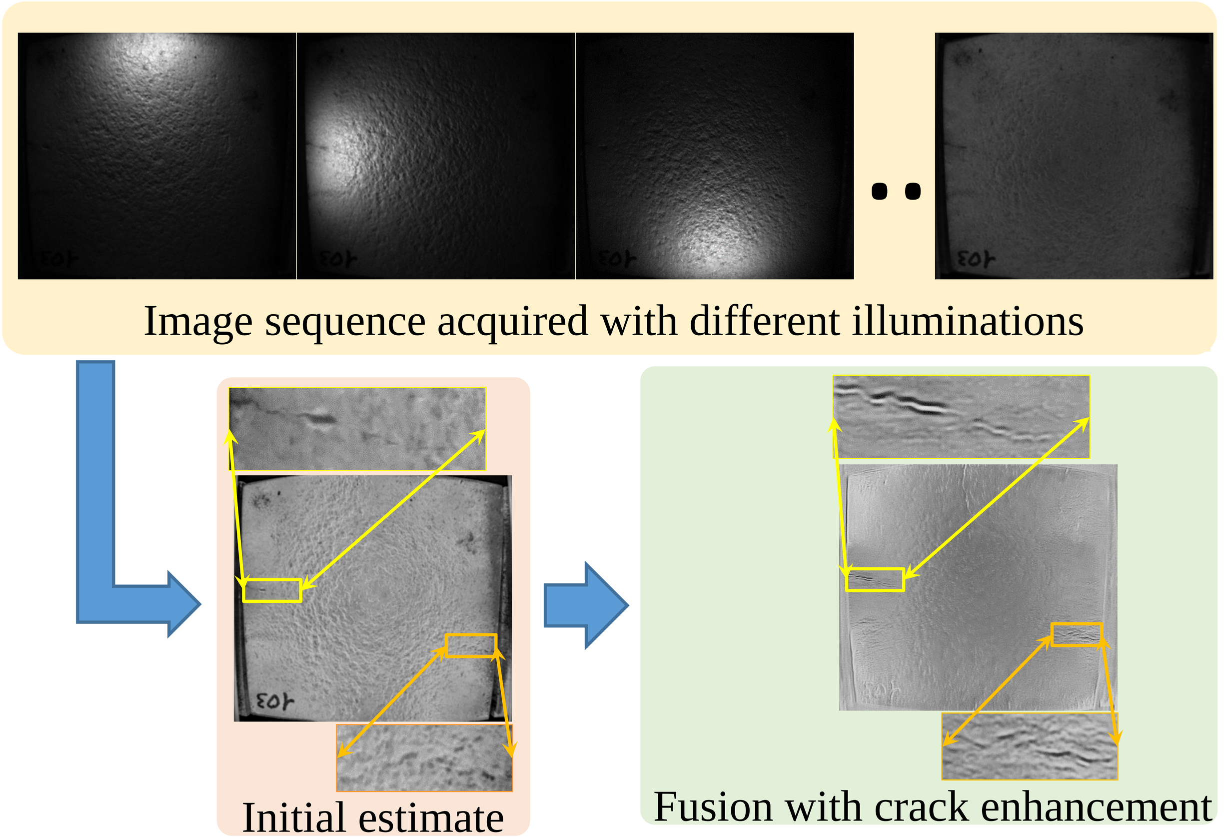
INTRODUCTION

Cracks can have better visibility under certain illumination conditions. Visual inspection of cracks from images can therefore benefit from several images wherein the object is illuminated from different directions.

The proposed method combines and enhances crack details from a sequence of multi-illumination images, to provide a single representative image, which can be helpful for visual inspection.

Our method uses cycle-consistent losses, such that the transformation from a multi-illumination sequence to a fused representative image, and back is consistent. Here, crack enhancement is achieved by constraining the transformations with loss networks that generate binary crack representations.



RELATED WORK

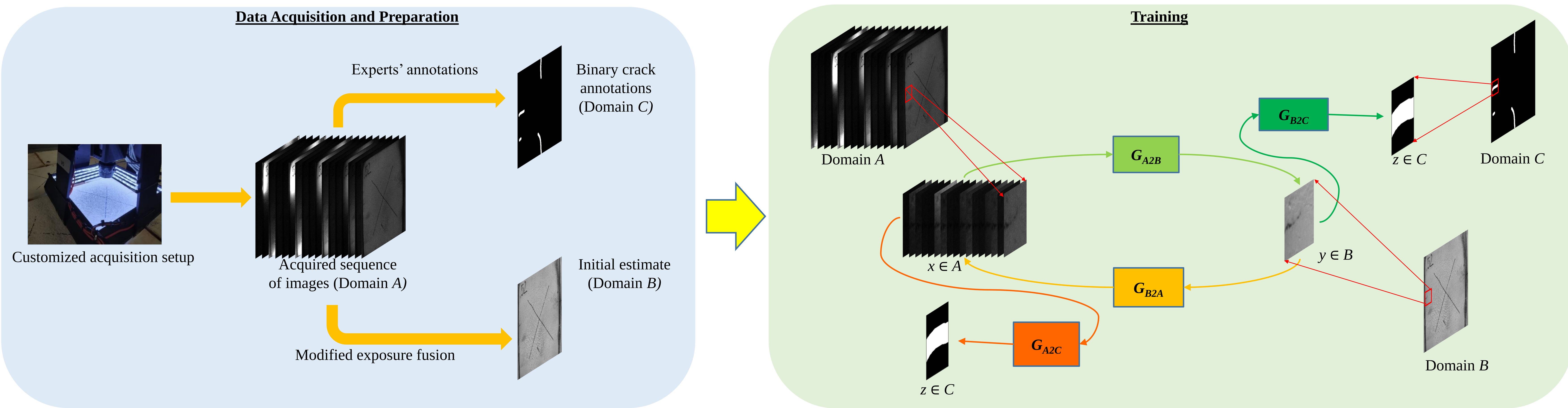
Multi-Exposure Fusion (MEF) [1-7]:

- Fusion of images acquired by varying exposure time.
- Change across pixels is consistent in the different images of the acquired sequence.

Our problem:

- Varying illumination directions can easily create noticeable shadows on cracks, as opposed to varying exposure time.
- Fusion of images acquired by varying illumination directions.
- Pixels are well exposed only in few but underexposed in most of the acquired images in the sequence.

PROPOSED METHOD



$$loss_{B2A} = BBCE(G_{A2C}(G_{B2A}(y)), z) + BBCE(G_{B2C}(G_{A2B}(G_{B2A}(y))), z) + BBCE(G_{A2C}(G_{B2A}(G_{A2B}(x))), z) + MAE(G_{A2B}(G_{B2A}(y)), y) + MAE(G_{B2A}(G_{A2B}(x)), x), \qquad loss_{A2C} = BBCE(x, z),$$

$$loss_{A2B} = BBCE(G_{B2C}(G_{A2B}(x)), z) + BBCE(G_{A2C}(G_{B2A}(G_{A2B}(x))), z) + BBCE(G_{B2C}(G_{A2B}(G_{B2A}(y))), z) + MAE(G_{B2A}(G_{A2B}(x)), x) + MAE(G_{A2B}(G_{B2A}(y)), y), \qquad loss_{B2C} = BBCE(y, z).$$

EXPERIMENT DETAILS

- Real-world industrial data of 88 ceramic tiles
- Every tile imaged with 65 different illuminations
- Image size: 1944 x 2592
- Patch size used for training: 128 x 128
- Model architecture based on U-Net [8]
- Trained from scratch for 2 epochs
  - NVIDIA RTX-2080 GPU
  - Batch size: 8
  - Adam optimizer
  - Learning rate:
    - 0.0001 for image generators
    - 0.00001 for crack generators

EVALUATION METRIC

Edge strength measured in term of Laplacian of Gaussian (LoG):

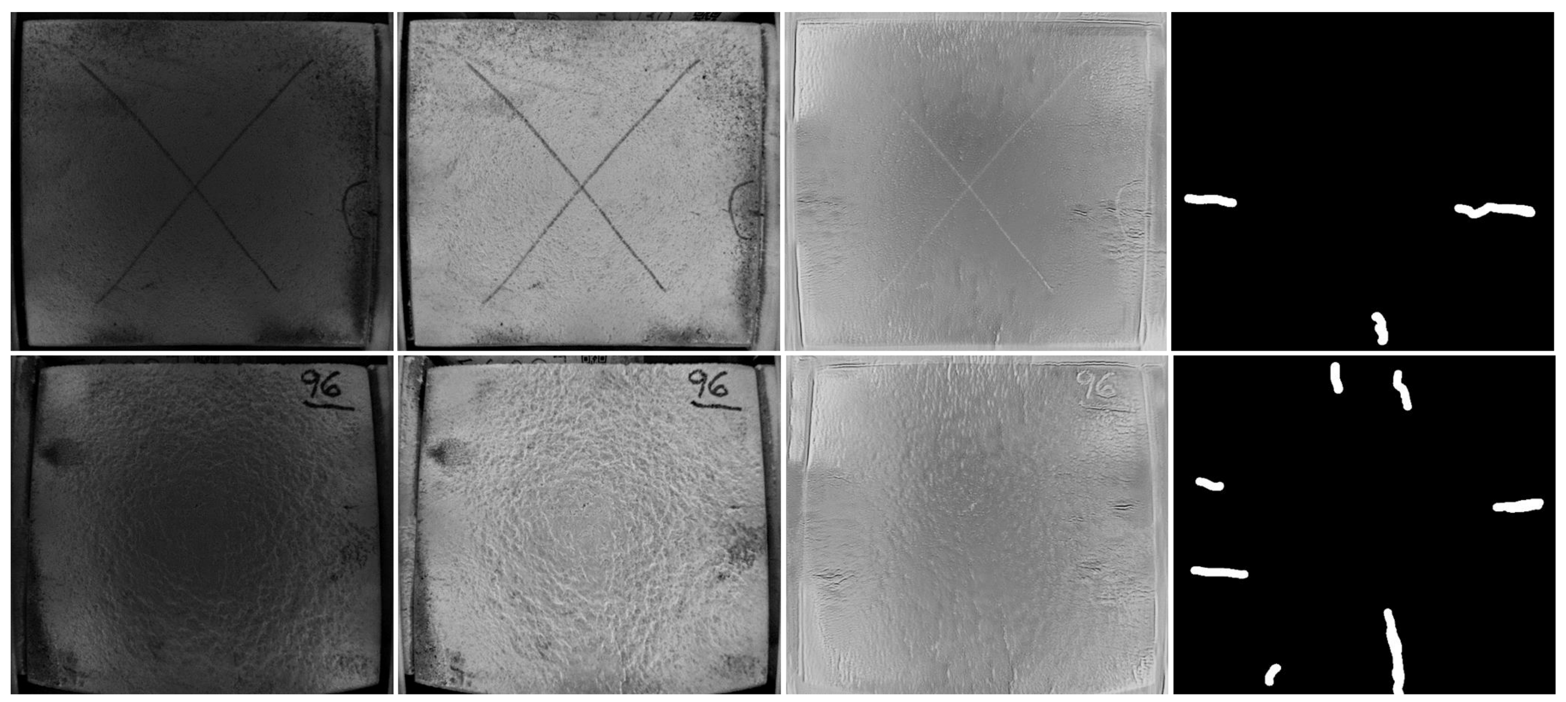
$$ES = \frac{mean(|L_p|)}{mean(|L_q|)},$$

$$p \in \Omega,\ q \in I,\ L = LoG(I),$$

L_p is value of L at pixel $p \in \Omega$,

L_q is value of L at pixel $q \in I$.

RESULTS



Fusion with a MEF method | Initial estimate | Proposed fusion with crack enhancement (G_{A2B}) | Ground truth crack annotations

Image #	MEF	Initial Estimate	Proposed (G_{A2B})
1	1.2369	1.2354	**2.6695**
2	1.0719	1.1380	**3.1600**
3	1.036	1.1272	**1.9077**
4	1.0825	1.1279	**1.7663**
5	1.0844	1.1723	**2.4617**
6	1.1637	1.0021	**2.3807**
7	0.9425	0.9081	**1.9220**
8	1.0956	0.9017	**2.4140**
9	1.0581	1.2385	**2.6135**

Performance comparison using *ES*. (The higher, the better)

CONCLUSIONS

- Proposed a method to combine and enhance crack details into a single representative
  - Fusion of several images acquired using different illuminations
- Trained generators using cycle-consistent losses
  - Cracks enhanced using crack generators as loss networks
  - Improved noticeability of cracks, helping visual inspection
- Addressed enhancement of pixels that are underexposed in most of the images of the acquired sequence
  - Proposed method better suited than MEF for fusion of multi-illumination images

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