Exposing Image Splicing with Inconsistent Local Noise Variances

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Broad Outline and Distribution of work

1) Global Noise Variance Estimation - Vineet
2) Local Noise Variance Estimation - Harsh
3) Splicing Detection and Evaluation - Ayush

Global Noise Variance Estimation

Original Image

Est. σ^2 = 9.8276e-06

With AWGN: $\mu = 0$, $\sigma^2 = 0.01$

Est. σ^2 = 0.0033

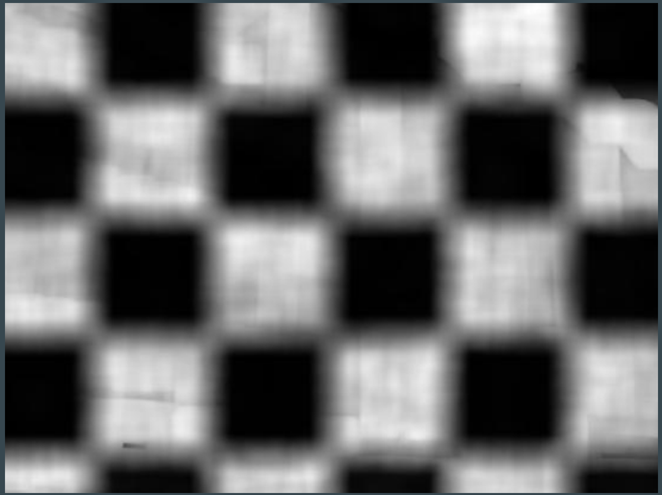
With AWGN: $\mu = 0$, $\sigma^2 = 0.02$

Est. σ^2 = 0.0061

Observation: Estimated values were accurate to relatively compare noise magnitudes. They were off by actual values only by a constant factor

Local Noise Variance Estimation

Chequered Noise Image



Local Noise Variance

Observation: Patches with added Noise are accurately distinguished from the patches with no noise added.

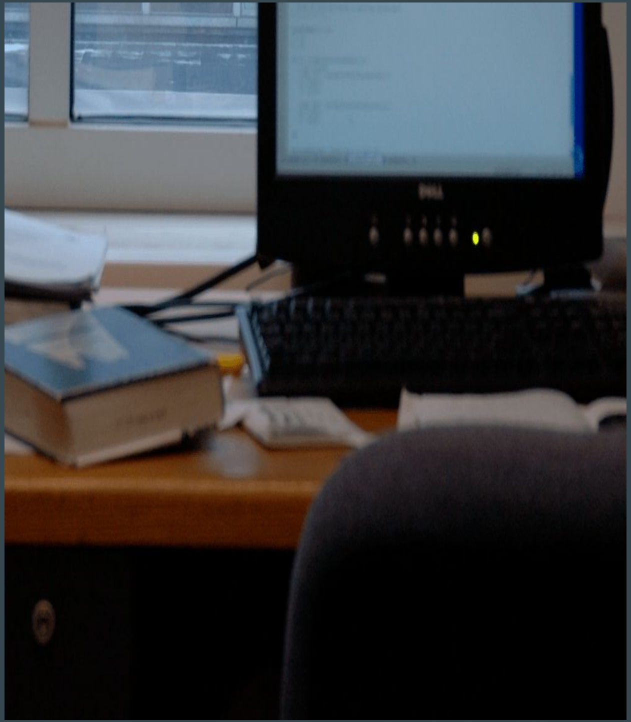
Local Noise Variance Estimation

Spliced Image

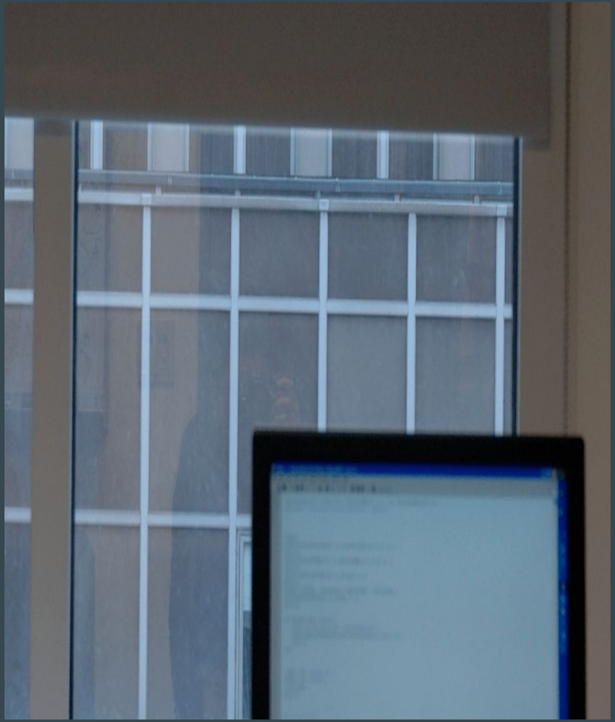
Local Noise Variance

Observation: The difference between the noise variances of the spliced patches and the original image can be seen.

Different noise variance for different camera models



Average local noise variance = 119.4



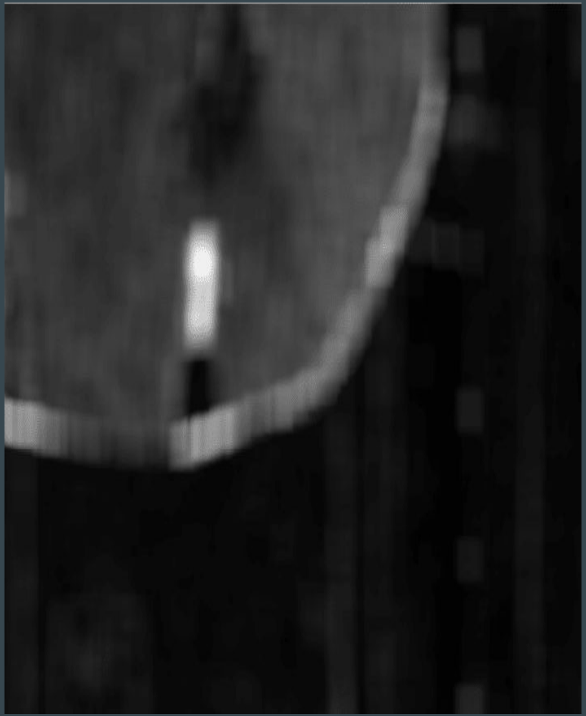
Average local noise variance = 115.6

Average local noise variance = 1.11

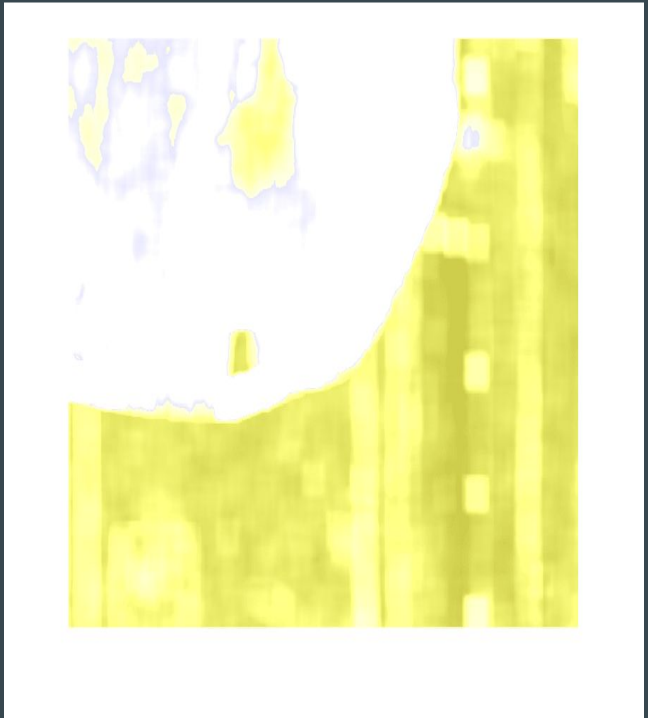
Image Splicing Detection

Images taken using different cameras thus having different noise variance

Spliced Image



Local Noise Variance



Segmentation

Comparison with related work

Disadvantages

1. It assumes the noise to be zero mean white Gaussian process that is additive and independent of the image
2. It does not give good results for JPEG compressed images
3. It assumes intrinsic noise variances are similar across different locations within the original image
4. It assumes that different images have different intrinsic noise variance

Advantages

1. The running time of this algorithm is much less than other algorithms for image splicing detection
2. It identifies spliced regions with higher accuracy down to the pixel level

THANK YOU

APPENDIX

$$\sqrt{\kappa} = \frac{\left\langle \sqrt{\tilde{\kappa}_k} \right\rangle_k \left\langle \frac{1}{(\tilde{\sigma}_k^2)^2} \right\rangle_k - \left\langle \frac{\sqrt{\tilde{\kappa}_k}}{\tilde{\sigma}_k^2} \right\rangle_k \left\langle \frac{1}{\tilde{\sigma}_k^2} \right\rangle_k}{\left\langle \frac{1}{(\tilde{\sigma}_k^2)^2} \right\rangle_k - \left\langle \frac{1}{\tilde{\sigma}_k^2} \right\rangle_k^2}$$

$$\sigma^2 = \frac{1}{\left\langle \frac{1}{\tilde{\sigma}_k^2} \right\rangle_k} - \frac{1}{\sqrt{\kappa}} \frac{\left\langle \sqrt{\tilde{\kappa}_k} \right\rangle_k}{\left\langle \frac{1}{\tilde{\sigma}_k^2} \right\rangle_k},$$

$$\begin{aligned} \sigma^2 &= \mu_2 - \mu_1^2 \\ \kappa &= \frac{\mu_4 - 4\mu_3\mu_1 + 6\mu_2\mu_1^2 - 3\mu_1^4}{\mu_2^2 - 2\mu_2\mu_1^2 + \mu_1^4} - 3. \end{aligned} \tag{6}$$

$$\begin{aligned} &\frac{1}{IJ}\Big[\mathcal{I}(\underbrace{\mathbf{x} \circ \cdots \circ \mathbf{x}}_{m \text{ times}})_{i+I,j+J} - \mathcal{I}(\underbrace{\mathbf{x} \circ \cdots \circ \mathbf{x}}_{m \text{ times}})_{i,j+J} \\ &- \mathcal{I}(\underbrace{\mathbf{x} \circ \cdots \circ \mathbf{x}}_{m \text{ times}})_{i+I,j} + \mathcal{I}(\underbrace{\mathbf{x} \circ \cdots \circ \mathbf{x}}_{m \text{ times}})_{i,j}\Big]. \end{aligned} \tag{7}$$