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Exposing Image Splicing with Inconsistent Local Noise Variances

Kurtosis Concentration

For a random variable x, we define its kurtosis as

$$\kappa = \frac{\tilde{\mu}_4}{(\sigma^2)^2} - 3$$

where $\sigma^2 = \mathcal{E}_x[(x - \mathcal{E}_x(x))^2]$, $\tilde{\mu}_4 = \mathcal{E}_x[(x - \mathcal{E}_x(x))^4]$

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Global Noise Variance Estimation

Global Noise Variance Estimation

$$\sqrt{\tilde{\kappa}} = \sqrt{\kappa}(\frac{\sigma_k^2 - \sigma^2}{\sigma_k^2})$$

Objective function :

$$min_{\sqrt{\kappa},\sigma^2} \sum_{k=1}^{K} [\sqrt{\tilde{\kappa}_k} - \sqrt{\kappa}(\frac{\sigma_k^2 - \sigma^2}{\sigma_k^2})]^2$$

where

κ: kurtosis of the original image in the k-th channel (constant)

$\tilde{\kappa}_k$: kurtosis of the noisy image in the k-th channel

σ_k: variance of the noisy image in the k-th channel

Global Noise Variance Estimation

Closed form solution to the objective function:

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

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

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Local Noise Variance Estimation

Local Noise Variance Estimation

The global noise variance estimator is then extended to a more general *local* noise variance estimator. Writing σ^2 and κ in terms of the raw moments, we have (*per pixel location per channel*):

$$\sigma^2 = \mu_2 - \mu_1^2$$

$$\kappa = \frac{\mu_4 - 4\mu_3\mu_1 + 6\mu_2\mu_1^2 - 3\mu_1^4}{\mu_2^2 - 2\mu_2\mu_1^2 + \mu_1^4} - 3$$

Local Noise Variance Estimation

The raw moment per window is estimated by spatial averaging:

$$\mu_m(\Omega^k_{(i,j)}) \approx \frac{1}{|\Omega^k_{(i,j)}|} \sum_{(i',j') \,\epsilon\, \Omega^k_{(i,j)}} x(i',j',k)^m$$

To make the process more efficient, the raw moment μ_m is computed using an *integrated image* as :

$$\frac{1}{IJ}[I(x^m)_{i+I,j+J} - I(x^m)_{i+I,j} - I(x^m)_{i,j+J} + I(x^m)_{i,j}]$$

with x^m being denoting pointwise multiplication m times

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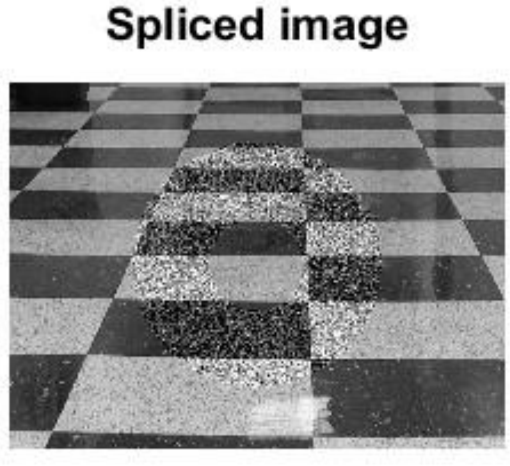
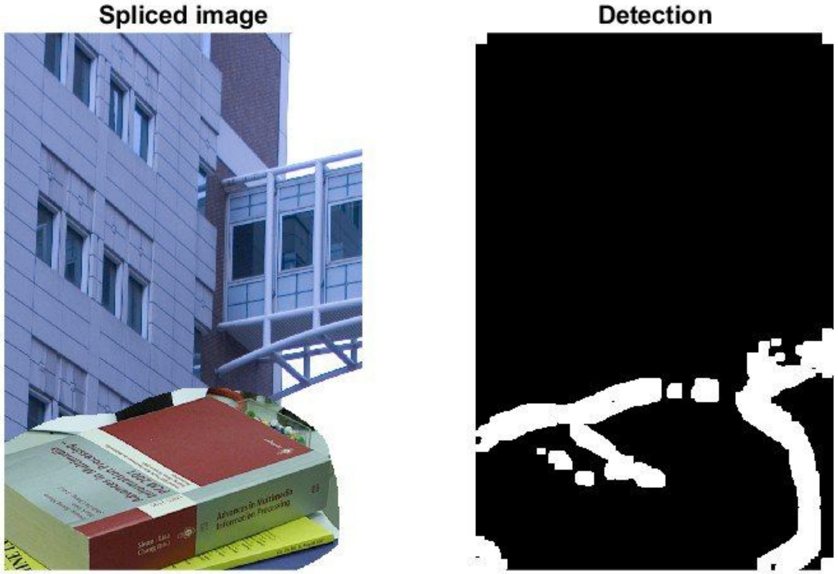
Results

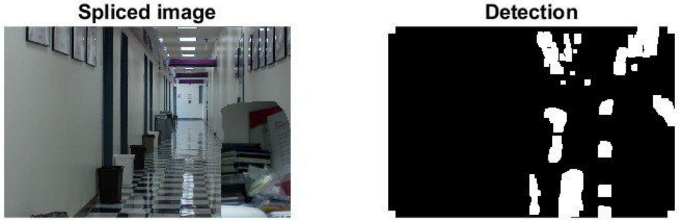
Different additive white Gaussian noise patterns

Different additive white Gaussian noise patterns

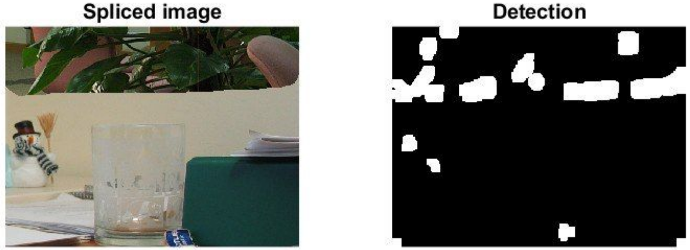


Results on Columbia Dataset

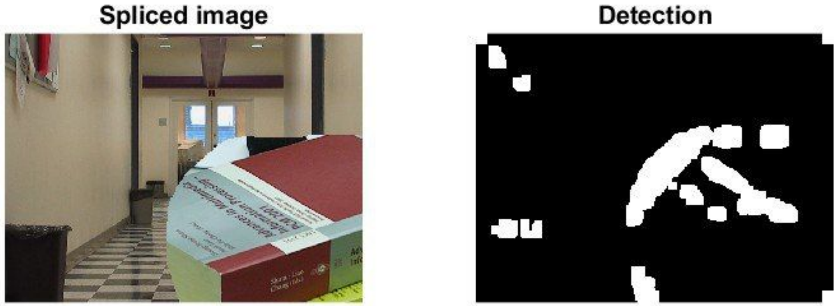


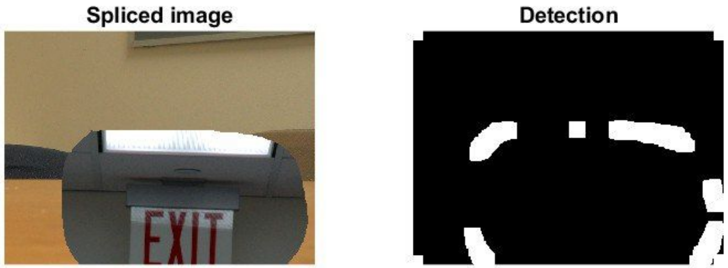


Results on Columbia Dataset

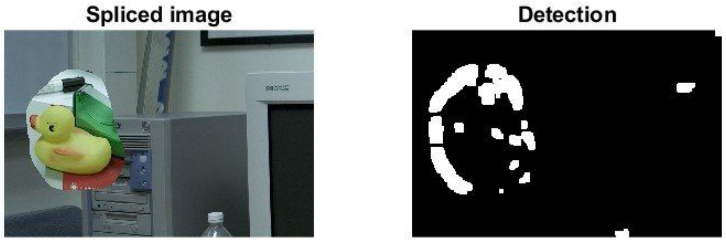


Results on Columbia Dataset

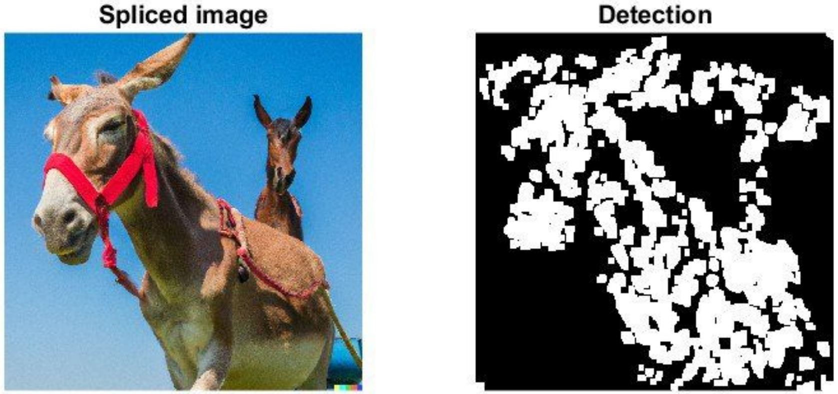


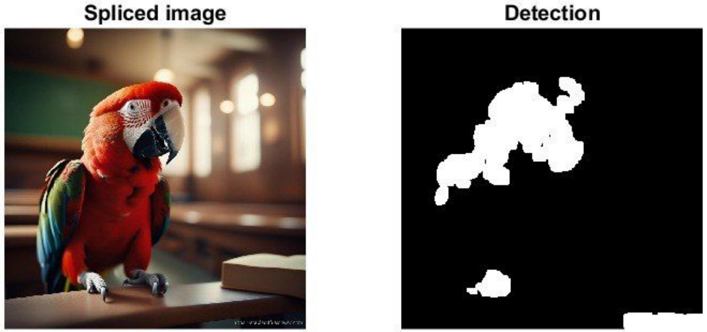


Results on Columbia Dataset

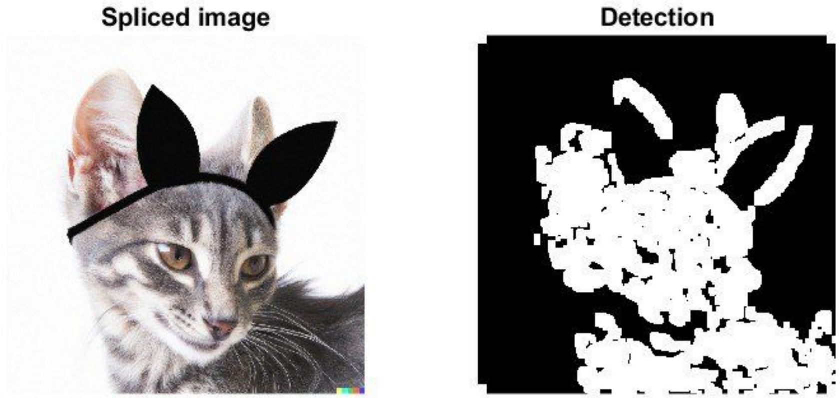


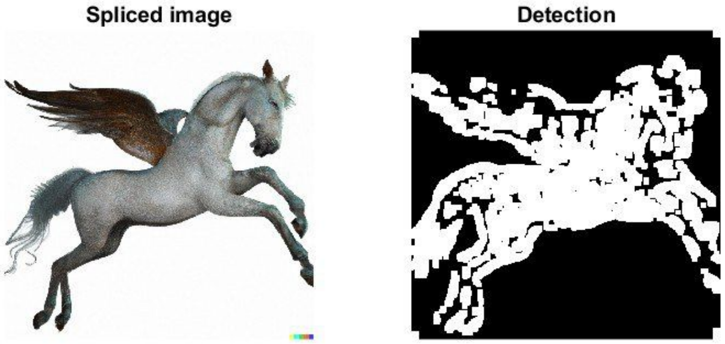
Results on AI Generated Dataset





Results on AI Generated Dataset





Observations

1. The method is sensitive to the choice of the band-pass filter. A filter that is too narrow may not capture enough noise information, while a filter that is too wide may introduce too much noise from other parts of the image.

2. Size of the corrupted area doesn’t have significant role in detection accuracy.

Observations

1. The last image is screenshot extracted from the paper's pdf. We believe significant information about the noise variances is lost leading to a wrong result.

2. This method relies on the assumption that the spliced region and the original image have different intrinsic noise variances. For cases where tampered image underwent heavy JPEG compression, for example, information of the difference in noise variances is lost.

3. For images with distinct texture and smooth regions, inhomogeneous local noise variance can cause the method to make false detections. (As seen in the tree detected in the first limitation example)

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