Detection of image splicing

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Our Project

For this project we have implemented a research paper titled "Exposing Image Splicing with Inconsistent Local Noise Variances" by Xunyu Pan, Xing Zhang and Siwei Lyu from the University at Albany, State University of New York.

Introduction

We attempt to expose image splicing by detecting inconsistencies in local noise variances by taking advantage of a statistical regularity of natural images - the kurtosis values of natural images in general band pass filtered domains are positive and tend to be close to a constant.

Kurtosis Concentration

For a random variable x, we define its kurtosis as

$$\kappa = \frac{\tilde{\mu}_4}{(\sigma^2)^2} - 3 \tag{1}$$

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

Global Noise Variance Estimation

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

Objective function :

$$min_{\sqrt{\kappa},\sigma^2} \sum_{k=1}^{K} [\sqrt{\tilde{\kappa}_k} - \sqrt{\kappa}(\frac{\sigma_k^2 - \sigma^2}{\sigma_k^2})]^2 \tag{3}$$

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:

$$\sqrt{\kappa} = \frac{\langle\sqrt{\tilde{\kappa}_k}\rangle_k \langle\frac{1}{(\tilde{\sigma_k}^2)^2}\rangle_k - \langle\frac{\sqrt{\tilde{\kappa}_k}}{\tilde{\sigma_k}^2}\rangle_k \langle\frac{1}{\tilde{\sigma_k}^2}\rangle_k}{\langle\frac{1}{(\tilde{\sigma_k}^2)^2}\rangle_k - \langle\frac{1}{\tilde{\sigma_k}^2}\rangle_k^2} \tag{4}$$

$$\sigma^2 = \langle\frac{1}{\tilde{\sigma_k}^2}\rangle_k - \frac{1}{\sqrt{\kappa}} \frac{\langle\sqrt{\tilde{\kappa}_k}\rangle_k}{\langle\frac{1}{\tilde{\sigma_k}^2}\rangle_k} \tag{5}$$

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*):

$$\sigma^2 = \mu_2 - \mu_1^2 \tag{6}$$

$$\kappa = \frac{\mu_4 - 4\mu_3\mu_1 + 6\mu_2\mu_1^2 - 3\mu_1^4}{\mu_2^2 - 2\mu_2\mu_1^2 + \mu_1^4} - 3 \tag{7}$$

Local Noise Variance Estimation

The raw moment per window is estimated by spatial averaging:

$$\mu_m(\Omega^k_{(i,j)}) \approx \frac{1}{|\Omega^k_{(i,j)}|} \sum_{(i',j') \; \epsilon \; \Omega^k_{(i,j)}} x(i', j', k)^m \tag{8}$$

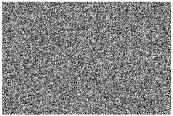
To make the process more efficient, the raw moment μ_m is computed using an *integrated image* as :

$$\frac{1}{IJ}[I(x^m)_{i+I,j+J} - I(x^m)_{i+I,j} - I(x^m)_{i,j+J} + I(x^m)_{i,j}] \tag{9}$$

with x^m being denoting pointwise multiplication m times

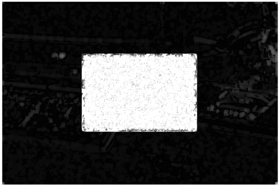
Different additive white Gaussian noise patterns

(a) Original image



(b) Gaussian noise model

(c) Corrupted image

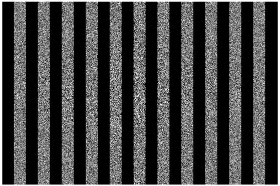


(d) Detection results

Figure: Results obtained for a Gaussian noise model

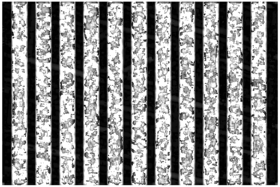
Different additive white Gaussian noise patterns

(a) Original image



(b) Gaussian noise model

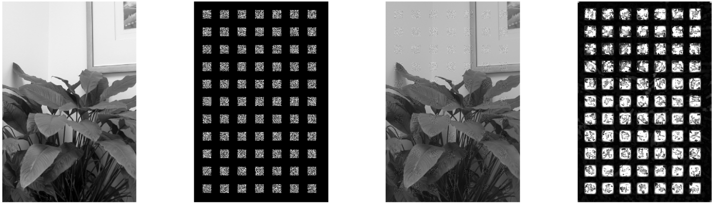
(c) Corrupted image



(d) Detection results

Figure: Results obtained for a striped Gaussian noise model

Different additive white Gaussian noise patterns



(a) Original image

(b) Gaussian noise model

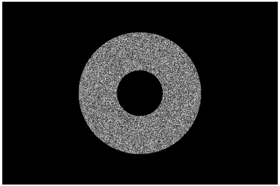
(c) Corrupted image

(d) Detection results

Figure: Results obtained for a checkerboard Gaussian noise model

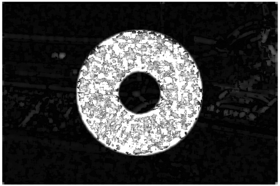
Different additive white Gaussian noise patterns

(a) Original image



(b) Gaussian noise model

(c) Corrupted image



(d) Detection results

Figure: Results obtained for an annular Gaussian noise model

True negatives

(a) Original Image

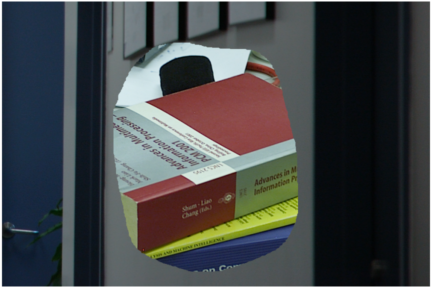
(b) No detection

True negatives

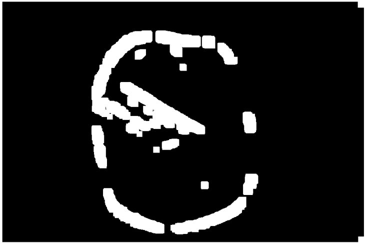
(a) Original Image

(b) No detection

Detection results on the Columbia dataset

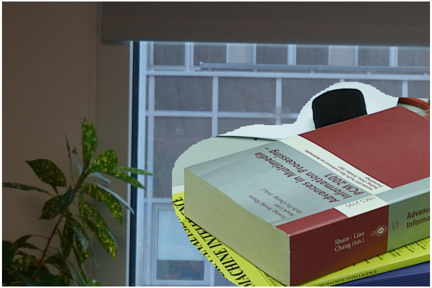


(a) Original Image



(b) Detection

Detection results on the Columbia dataset

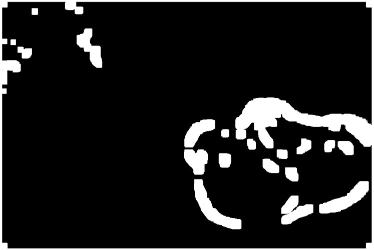


(a) Original Image

(b) Detection

Detection results on the Columbia dataset

(a) Original Image



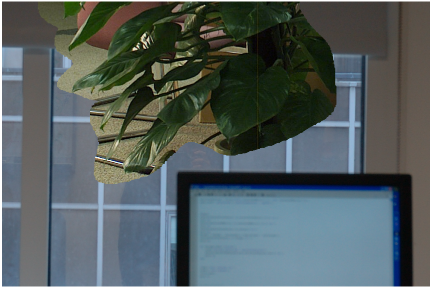
(b) Detection

Detection results on the Columbia dataset

(a) Original Image

(b) Detection

Detection results on the Columbia dataset



(a) Original Image

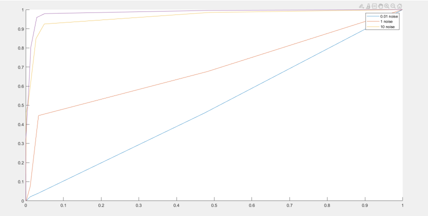
(b) Detection

Detection results on the Columbia dataset

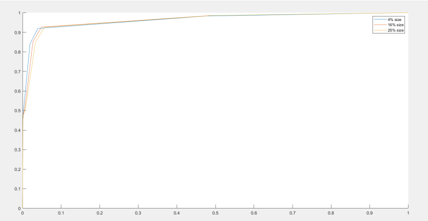
(a) Original Image

(b) Detection

Quantitative Evaluation



(a) Added noise levels



(b) Spliced region sizes

Figure: ROC curves of detection accuracy v.s. false positive rates for (left) different noise variances and (right) different sizes of the spliced region in percentage of the size of the original image.

Observations

1) True positives dominate false positive for high variance noise.

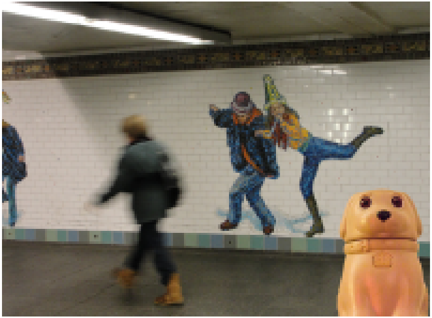
2) Size of the corrupted area doesn't have significant role in detection accuracy.

Limitations

(a) Original Image

(b) Detection

Limitations



(a) Original Image

(b) Detection

Limitations

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)

Contributions

A. Kranthi - Application of DCT
D. Heemmanshuu - Noise variance estimation and Image splicing detection
Manoj Varma - Quantitative Evaluation