digital image forensics:

I know what you did in the last Photoshop session

Siwei Lyu

Computer Science Department
University at Albany, State University of New York

National Laboratory of Pattern Recognition
Chinese Academy of Science -- 07/02/2013
“seeing is believing”
“seeing is believing”?
CG or photo

detecting image steganography

art forensics

detecting region duplication

detecting image splicing

vignetting correction & lens authentication
image splicing
splicing detection
• double JPEG compression [Lin et.al., 2009]
• camera-response function [Hsu & Chang, 2007]
• statistics-based feature classification [Baryam et.al. 2006]

splicing detection using blind local noise variance estimation
• original image & device independent
• efficiency & accuracy

[Popescu & Farid, 2004; Liu et.al, 2010; Mahdian & Saic, 2009]
question:

how to estimate $\sigma^2$ from observed $\tilde{y}$?
The orthonormal band-pass filter domain*:

\[ \tilde{y} = \tilde{x} + \tilde{n} \]

\[ \text{var}(\tilde{n}) = \sigma^2 \]

- noisy subband
- noise free subband
- i.i.d. noise

\[ \approx \text{Gaussian} \]

(central limit theorem)

**question:**

how to estimate \( \sigma^2 \) from observed \( \tilde{y} \)?

**popular solution:**

maximum absolute deviation (MAD) [Donoho, 1995]

*such as orthogonal wavelet, or DCT AC filters
kurtosis \[ \kappa = \frac{\hat{\mu}_4}{\hat{\mu}_2^2} - 3 \]

\[ \hat{\mu}_2 = \mathcal{E}_x \left\{ (x - \mathcal{E}_x \{x\})^2 \right\} \]

\[ \hat{\mu}_4 = \mathcal{E}_x \left\{ (x - \mathcal{E}_x \{x\})^4 \right\} \]

[Burt & Adelson, 1984; Fields, 1986]
relation of kurtosis and noise variance

\[
\tilde{\kappa}_k = \kappa_k \left( \frac{\tilde{\sigma}_k^2 - \sigma^2}{\tilde{\sigma}_k^2} \right)^2
\]

natural images have positive kurtosis in subbands

\[
\sqrt{\tilde{\kappa}_k} = \sqrt{\kappa_k} \left( \frac{\tilde{\sigma}_k^2 - \sigma^2}{\tilde{\sigma}_k^2} \right)
\]
<table>
<thead>
<tr>
<th>Subband Number</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td></td>
</tr>
<tr>
<td>150</td>
<td></td>
</tr>
<tr>
<td>200</td>
<td></td>
</tr>
<tr>
<td>250</td>
<td></td>
</tr>
</tbody>
</table>

\[
\tilde{\kappa}_k = \kappa_k \left( \frac{\tilde{\sigma}_k^2 - \sigma^2}{\tilde{\sigma}_k^2} \right)
\]

[Bethge, JoSA, 2006; Lyu & Simoncelli, NIPS, 2008; Zoran & Weiss, ICCV, 2009]
\[
\sqrt{\kappa_k} \approx \sqrt{\kappa_k} \left( \frac{\tilde{\sigma}_k^2}{\hat{\sigma}_k^2} \right)
\]

**objective function**

\[
\min_{\sqrt{\kappa}, \sigma^2} \sum_{k=1}^{K} \left[ \sqrt{\kappa_k} - \sqrt{\kappa} \left( \frac{\tilde{\sigma}_k^2}{\hat{\sigma}_k^2} \right) \right]^2
\]

**closed-form solution**

\[
\sqrt{\kappa} = \frac{\langle \sqrt{\kappa_k} \rangle_k \langle \frac{1}{(\hat{\sigma}_k^2)^2} \rangle_k - \langle \sqrt{\kappa_k} \rangle_k \langle \frac{1}{\hat{\sigma}_k^2} \rangle_k}{\langle \frac{1}{(\hat{\sigma}_k^2)^2} \rangle_k - \langle \frac{1}{\hat{\sigma}_k^2} \rangle_k^2}
\]

\[
\sigma^2 = \frac{1}{\langle \frac{1}{\hat{\sigma}_k^2} \rangle_k} - \frac{1}{\sqrt{\kappa}} \frac{\langle \sqrt{\kappa_k} \rangle_k}{\langle \frac{1}{\hat{\sigma}_k^2} \rangle_k},
\]
| PSNR | Kodak | | | UCID | | | | Van Hateren | |
|------|-------|---|-----|------|---|-----|------|---|-----|------|---|-----|------|---|-----|------|
|      | PZL   | ZW | MAD | PZL  | ZW | MAD | PZL  | ZW | MAD | PZL  | ZW | MAD | PZL  | ZW | MAD |
| 20dB | 20.03 | 20.29 | 19.82 | 20.06 | 20.37 | 19.69 | 20.00 | 20.10 | 19.96 |
| 30dB | 30.16 | 30.54 | 28.97 | 30.46 | 31.15 | 28.40 | 30.01 | 30.19 | 29.74 |
| 40dB | 41.08 | N/A | 36.09 | 41.71 | N/A | 34.63 | 40.46 | 43.24 | 38.77 |
| 50dB | 46.01 | N/A | 39.72 | 45.93 | N/A | 37.45 | 48.70 | N/A | 45.62 |

PZL: this work
ZW: [Zoran & Weiss, 2009]
MAD: [Donoho & Johnston, 1996]
closed-form solution

$$\sqrt{\kappa} = \frac{\langle \sqrt{\kappa} \rangle_k \langle \frac{1}{(\bar{\sigma}_k^2)^2} \rangle_k - \langle \sqrt{\kappa} \rangle_k \langle \frac{1}{\bar{\sigma}_k^2} \rangle_k \langle \frac{1}{\bar{\sigma}_k^2} \rangle_k}{\langle \frac{1}{(\bar{\sigma}_k^2)^2} \rangle_k - \langle \x2/ \rangle_k}$$

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

relation with raw moments

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

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

$$\mu_m = \mathcal{E}_x \{ x^m \}$$
\[ \mu_m \left( \Omega_{i,j}^{I,J} \right) \approx \frac{1}{IJ} \sum_{(i',j') \in \Omega_{i,j}} x_{i',j'}^m \]

\[ \sum_{(i',j') \in \Omega_{i,l}^{I,J}} x_{i',j'} = \mathcal{I}(x)_{i+I,j+J} - \mathcal{I}(x)_{i,j+I} - \mathcal{I}(x)_{i+I,j} + \mathcal{I}(x)_{i,j} \]

\[ \mu_m (\Omega_{i,j}^{I,J}) \approx \frac{1}{IJ} \left[ \mathcal{I}(\underbrace{x \circ \cdots \circ x}_{m \text{ times}})_{i+I,j+J} - \mathcal{I}(\underbrace{x \circ \cdots \circ x}_{m \text{ times}})_{i,j+I} - \mathcal{I}(\underbrace{x \circ \cdots \circ x}_{m \text{ times}})_{i+I,j} + \mathcal{I}(\underbrace{x \circ \cdots \circ x}_{m \text{ times}})_{i,j} \right] . \]
detecting image splicing

Local Noise Levels

Low Noise Variance
Binary Mask

High Noise Variance
Splicing Detection

image source: worth1000.com
further discussion

- qualitative evaluation and comparison
- robustness w.r.t. JPEG/geometry transforms
- false detection and miss detection
  - modeling local covariance matrices
- applicability
  - signal level automatic splicing detection
- counter-measures?
summary

- image splicing may be detected with inconsistent local noise variances
- noise variances can be estimated using kurtosis concentration in band-pass filter domains
- local noise variance estimation can be further accelerated by using integral image
- future works
  - theoretical understanding of kurtosis concentration
  - estimation of local covariance matrices
CG or photo

[Lyu & Farid, IEEE TSP, 2005]

detecting image steganography

[Lyu & Farid, IEEE TIFS, 2006],
IEEE SPS Best Paper Award, 2010

vignetting correction & lens authentication

[Lyu, ACM MM&Sec, 2010]

art forensics

[Lyu et.al., PNAS, 2005]

detecting region duplication

[Pan & Lyu., IEEE TIFS, 2011]

detecting image splicing

[Pan et.al., ICCP, 2012]
detecting region duplication
scale invariant feature transform (SIFT)
[Lowe, 2004]

detecting region duplication

[Pan and Lyu, IEEE TIFS, 2011]
detecting region duplication

matching feature subsets

[Pan and Lyu, IEEE TIFS, 2011]
detecting region duplication

RANSAC matching
region similarity

detecting region duplication

[Pan and Lyu, IEEE TIFS, 2011]
source: [Farbman et al., SIGGRAPH 09]

[Pan and Lyu, IEEE TIFS, 2011]
source: [Farbman et al., SIGGRAPH 09]
Rhein II by Andreas Gursky
source: times.com
summary

- digital images are subject to tampering
- image forgeries can be detected
  - region duplication
  - image splicing
- counter-measures?
Thank you!

This work is supported by
- a U.S. National Science Foundation Faculty Early Career Award (CAREER)
- U.S. National Science Foundation research grant IIS-1208463
- U.S. National Science Foundation research grant CCF-1319800
- a U.S. National Institute of Justice research grant 12-087245
- a General Electronic Research contract
- SUNY Albany Faculty Research Award Program
I am currently looking for a post-doc to work on projects related with digital image forensics, natural image statistics, computer vision and machine learning. The post starts September 2013, and has a duration of three years upon yearly renewal. The annual salary is $50K with full benefit. The University will provide support for H1-B visa application.

The requirements include:
- completed Ph.D. degree in CS or EE on or before December 2013
- strong publication records
- strong self-motivation
- good communication skills in English

Contact: Dr. Siwei Lyu (slyu@albany.edu) with a complete CV