Digital Image Forgery Detection by Local Statistical Models

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Outline

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Introduction – What Problem Do We Address ?

Specific Problem of Digital Forensic:

to expose traces of possible tampering in a given image of unknown origin (blind approach)

examples of available methods:

- copy-move forgery detection
- identification of lighting inconsistencies
- detection of periodicities introduced by resampling
- evaluation of JPEG quantization artifacts
- detection of locally different statistical properties

STATE OF ART:

- available methods do not allow strict conclusions
- accuracy decreases with lossy compression formats
- results of detection are not always convincing
- only specific types of tampering may be identified

Idea of the Method

WE PROPOSE:

detection of suspect regions by unusual local statistical properties

Motivation:

some specific features of images (spectral, textural) can be described locally by statistical properties of pixels in a small sliding window

digitized color image: $\mathcal{Z} = [\mathbf{z}_{ij}]_{i=1}^{I}\,_{j=1}^{J}$

$\mathbf{z}_{ij} = (z_{ij1}, z_{ij2}, z_{ij3}) \in \langle 0, 255 \rangle^3 \quad \approx$ three spectral values for each pixel

$\mathbf{x} \approx$ spectral RGB pixel values of the window in a fixed arrangement

$\mathbf{x} = (x_1, x_2, \ldots, x_N) \in \langle 0, 255 \rangle^N$

Idea:

- estimation of the multivariate probability density $P(\mathbf{x})$
- identification of untypical locations by low probability

Local Statistical Mixture Model

STATISTICAL MODEL: Gaussian mixture of product components

$$P(\mathbf{x}) = \sum_{m=1}^{M} w_m F(\mathbf{x}|\boldsymbol{\mu}_m, \boldsymbol{\sigma}_m) = \sum_{m=1}^{M} w_m \prod_{n=1}^{N} f_n(x_n|\mu_{mn}, \sigma_{mn})$$

$$f_n(x_n|\mu_{mn}, \sigma_{mn}) = \frac{1}{\sqrt{(2\pi)}\sigma_{mn}} \exp\left\{ -\frac{(x_n-\mu_{mn})^2}{2\sigma_{mn}^2} \right\}$$

MODEL ESTIMATION: by means of EM algorithm EM Algorithm

Invariance Property:

log-likelihood image is invariant with respect to arbitrary linear transform of the grey scale of the original image Proof

REMARK: The component means $\boldsymbol{\mu}_m$ are computed as weighted averages of the sample vectors $\mathbf{x} \in \mathcal{S}$ (cf. EM algorithm) and therefore they are rather smooth without high frequency details. Thus, inserted image portion with suppressed high frequencies will be more probable.

LOG-LIKELIHOOD IMAGE

$\log P(\mathbf{x})$ $\approx$ **measure of typicality of the window patch x**
$\log P(\mathbf{x})$ $\approx$ **displayed as grey level at the central pixel of the window**

INTERPRETATION: **dark pixels** corresponding to the low values of $\log P(\mathbf{x})$ may indicate "untypical" or "suspect" locations of the image

Mechanisms of Forgery Detection:

- unusual spectral properties of small areas will be less probable
- unusual textural properties of small areas will be less probable
- blurred regions will appear more probable **(!)** because of missing high-frequency details

scaling of log-likelihood image: $\log P(\mathbf{x}) \in \langle \mu_0 - 2 * \sigma_0; \ \mu_0 + 2 * \sigma_0 \rangle$

REMARK: In high-dimensional spaces the density values $P(\mathbf{x})$ of adjacent windows may differ by several orders; therefore the log-likelihood values $\log P(\mathbf{x})$ are more suitable as a measure of typicality.

Computational Details of the Method

NUMERICAL EXPERIMENTS:

- small square window of 5x5 pixels with trimmed corners
- (large windows tend to smooth out small details)
- 21 window pixels in three colors imply the model dimension N=63
- the estimated mixture density $P(\mathbf{x})$ describes the statistical properties of the 63 color sample values x_n of window patch
- training data set $\mathcal{S}$ is obtained by scanning the image with the search window
- the source texture images imply training data sets of size $|\mathcal{S}| \approx 10^6$
- number of components $M \approx 10^2$
- EM algorithm: random initialization, stopping rule: relative increment threshold ($\approx$ 10 - 20 iterations)
- **computing time:** picture: 3M pixels, model: M=20 components, dimension: N=63, 20 iterations $\approx$ 15 minutes (standard PC)

Image Forgery Detection - Original Image

Original image including an inserted oval region in the left-upper part

Image Forgery Detection - Log-likelihood Image

The oval part in the left-upper corner having somewhat different textural properties becomes distinctly lighter in the log-likelihood image

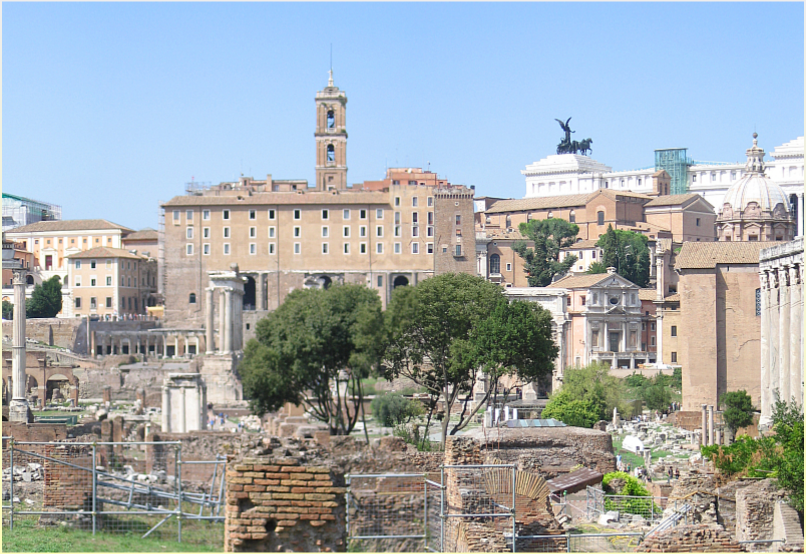
Image Forgery Detection - Original Image

Original image assembled from two parts by autostitch software.

Image Forgery Detection - Log-likelihood Image

The slightly blurred left part becomes lighter in the log-likelihood image.

Image Forgery Detection - Original Image



Original picture assembled from three parts by autostitch software.

Image Forgery Detection - Log-likelihood Image

The medium slightly blurred (incorrectly focused) part becomes lighter.

Concluding Remarks

Properties of the Log-Likelihood Image

- component means computed as weighted averages of data vectors are rather smooth
- log-likelihood image is invariant with respect to arbitrary linear transforms of the grey scales
- even small differences in brightness, resolution, frequency content or texture may cause visible changes in the log-likelihood image

Identification of Suspect Regions by Local Statistical Model:

- forgery detection by local statistical models is a blind method
- applicable to images of unknown origin without any prior information
- no specific type of image tampering is assumed
- capable to expose image manipulations of various kinds
- reasonably resistent to lossy information compression

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Estimation of Local Statistical Models

dat set: $\mathcal{S} = \{\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(K)}\}$ $\approx$ by shifting observation window

components: $$F(\mathbf{x}|\boldsymbol{\mu}_m, \boldsymbol{\sigma}_m) = \prod_{n=1}^{N} \frac{1}{\sqrt{(2\pi)}\sigma_{mn}} \exp\left\{ -\frac{(x_n - \mu_{mn})^2}{2\sigma_{mn}^2} \right\}$$

log-likelihood criterion: $$L = \frac{1}{|\mathcal{S}|} \sum_{\mathbf{x}\in\mathcal{S}} \log[\sum_{m=1}^{M} w_m F(\mathbf{x}|\boldsymbol{\mu}_m, \boldsymbol{\sigma}_m)]$$

EM algorithm:

$$q(m|\mathbf{x}) = \frac{w_m F(\mathbf{x}|\boldsymbol{\mu}_m, \boldsymbol{\sigma}_m)}{\sum_{j=1}^{M} w_j F(\mathbf{x}|\boldsymbol{\mu}_j, \boldsymbol{\sigma}_j)}, \quad \mathbf{x} \in \mathcal{S}, \ m = 1, 2, \ldots, M$$

$$w_m^{'} = \frac{1}{|\mathcal{S}|} \sum_{\mathbf{x}\in\mathcal{S}} q(m|\mathbf{x}), \qquad \mu_{mn}^{'} = \frac{1}{\sum_{\mathbf{x}\in\mathcal{S}} q(m|\mathbf{x})} \sum_{\mathbf{x}\in\mathcal{S}} x_n q(m|\mathbf{x})$$

$$(\sigma_{mn}^{'})^2 = -(\mu_{mn}^{'})^2 + \frac{1}{\sum_{\mathbf{x}\in\mathcal{S}} q(m|\mathbf{x})} \sum_{\mathbf{x}\in\mathcal{S}} x_n^2 q(m|\mathbf{x}), \ n = 1, 2, \ldots, N$$

Return

Invariance with Respect to Grey-Level Transformation

Invariance Property of Product Mixtures:

Assume that a linear transform is applied both to the data set $\mathcal{S}$ and to some estimated mixture parameters. Then the transformed parameters also satisfy the EM iteration equations.

Proof: The transformed data and transformed mixture parameters

$$\mathbf{y} = T(\mathbf{x}), \; y_n = a x_n + b, \; \mathbf{x} \in \mathcal{S}, \quad \tilde{\mu}_{mn} = a\mu_{mn} + b, \; \tilde{\sigma}_{mn} = a\sigma_{mn}$$

can be shown to satisfy the EM iteration equations since

$$q(m|\mathbf{y}) = q(m|\mathbf{x}), \quad \mathbf{x} \in \mathcal{S}, \quad \tilde{w}_m = w_m, \quad m \in \mathcal{M}$$

$$F(\mathbf{y}|\tilde{\boldsymbol{\mu}}_m, \tilde{\boldsymbol{\sigma}}_m) = \frac{1}{a^N} F(\mathbf{x}|\boldsymbol{\mu}_m, \boldsymbol{\sigma}_m), \quad \tilde{P}(\mathbf{y}) = \frac{1}{a^N} P(\mathbf{x})$$

and the corresponding log-likelihood values differ only by a constat

$$\log \tilde{P}(\mathbf{y}) = -N \log a + \log P(\mathbf{x}), \quad \mathbf{x} \in \mathcal{S}$$

which is removed by fixing the displayed grey-level interval

Return

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