Camera identification from sensor fingerprints: why noise matters

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Outline

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1. Introduction
   - Identification of source cameras
   - Recent work
2. Solution
   - Fingerprint Estimation
   - Fingerprint Detection
   - Evaluation
3. Discussion
4. Further Reading

Image Forensics

- detecting the fingerprint:
  - prove that a certain camera took a given image
  - prove that two images were taken by the same device
  - image is natural and not a computer rendering
- absence of the fingerprint in individual image regions
  - maliciously replaced parts of the image (integrity verification)

[Fridrich, 2009]

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Image Forensics

- strength or form of the fingerprint
  - reconstruct processing history
  - e.g. fingerprint as template to estimate geometrical processing (scaling, cropping, or rotation)
  - non-geometrical operations identified by influenced strength of the fingerprint
- spectral and spatial characteristics of the fingerprint
  - identify the camera model
  - distinguish between a scan and a digital camera image

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[Fridrich, 2009]

Requirements on a camera identifier (fingerprint)

high dimensionality to cover large number of cameras

uniqueness no two cameras have the same fingerprint

stability over time and typical range of physical conditions under which cameras operate

robustness to common image processing

- brightness, contrast, and gamma correction
- filtering
- format conversions
- resampling and JPEG compression

universality virtually all digital cameras have it

[Goljan, 2008]

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Detecting forgeries - visual sensor classification

- detecting **duplicated image regions** [Popescu and Farid, 2004a]
- using **statistics** to reveal forgeries [Popescu and Farid, 2004b]
- detecting traces of **resampling** [Popescu and Farid, 2005a]
- forgeries in **scientific** images [Farid, 2006]
- intrinsic **lens radial distortion** [Choi et al., 2006]
- **color filter array interpolation** [Popescu and Farid, 2005b, Bayram et al., 2006, Swaminathan et al., 2007]
- imaging **sensor types** [Khanna et al., 2007a]
- **cell phone** cameras [Sankur et al., 2007]
- sensor **dust** characteristics [Dirik et al., 2007b]

Camera identification: Noise patterns

- sensor **imperfections** [Lukáš et al., 2005]
- sensor **noise** [Lukáš et al., 2006a, Lukáš et al., 2006b, Chen et al., 2007a, Khanna et al., 2007b, Chen et al., 2008]
- noise features [Gou, 2007]
- common source digital camera from **image pairs** [Goljan et al., 2007]
- CCD photo response non-uniformity (**PRNU**)[Chen et al., 2007b]
- improvements... [Sutcu et al., 2007]
- noise in **scaled** and **cropped** images [Goljan and Fridrich, 2008]
- **printed** images [Goljan et al., 2008]
- camera **model** identification [Filler and Fridrich, 2008]

Photo Response Non-Uniformity (PRNU)

- (Main) research group: Lukáš, Chen et al., Goljan, Fridrich, Filler, et al.
- PRNU is injected into the image **during acquisition**
  - before the signal is quantized
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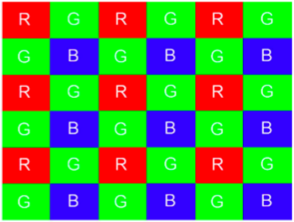
Sensor Output Model - Intuitive View

1. **light** cast by the camera optics projected onto pixel grid of the imaging sensor
2. **amplification** and **quantization**
3. **Color Filter Array**
   - interpolation (or demosaicking)
   - color correction, gamma correction



Finally:

- evt. filtering (de-noising, sharpening)
- JPEG: quantization

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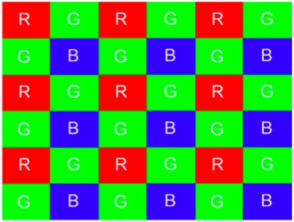

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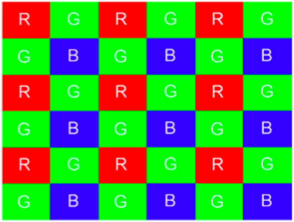

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Sensor Output Model - Mathematic Model

$$I = g^{\gamma}[(1 + K)Y + \Omega]^{\gamma} + Q \qquad (1)$$

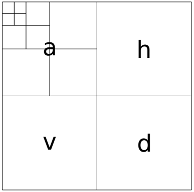
- I quantized signal before demosaicking
- g gain factor
- γ gamma correction factor
- K zero-mean noise-like signal - SENSOR FINGERPRINT
- Ω other noise sources
- Q distortion by quantization and/or compression
- Y scene light intensity

Outline

Fingerprint Estimation

- Sensor fingerprint is a noise-like signal.
- Sensor noise is … well, noise.
- How to find noise? Denoise the image, then diff it to the original.

Wavelet based Noise-Filter[Mihcak et al., 1999]



- Do a 4th-level wavelet decomposition (db8)
- For each high-frequency sub-band, and for each window size $w \in \{3, 5, 7, 9\}$, estimate local variance:

$$\hat{\sigma}_w^2[i,j] = \max(0, \frac{1}{w^2} \sum_{(i,j) \in N} h^2[i,j] - \sigma_0^2)$$

- Pick the smallest in each point, that's our $\hat{\sigma}^2[i,j]$.
- Apply a Wiener filter: $h_{\text{den}}[i,j] = h[i,j] \frac{\hat{\sigma}^2[i,j]}{\hat{\sigma}^2[i,j] + \sigma_0^2}$.
- Inverse the wavelet transform.

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Fingerprint Estimation, II

- Noise residual of one image is now $W = I - F(I)$.
- Fingerprint for many images? $\Rightarrow$ Average them.
- Observation: brighter regions contain more of the fingerprint. $\Rightarrow$ Weight them.

$$\widehat{K} = \frac{\sum_{i=1}^{n} W_i I_i}{\sum_{i=1}^{n} (I_i)^2}$$

- $\widehat{K}$ is our camera fingerprint.

[Goljan, 2008]

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Fingerprint Estimation, III

- PRNU is **unique** to the sensor.
- Other artifacts are **shared** among cameras of same model or sensor design.
- $\widehat{K}$ contains all **systematic** components in images, that is, artifacts introduced by:
  - color interpolation
  - JPEG compression
  - on-sensor signal transfer
  - sensor design

[Fridrich, 2009]

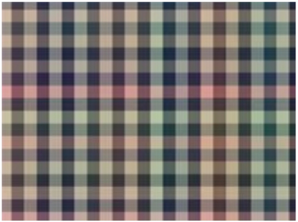
Suppress artifacts by camera model or sensor design

- Artifacts are periodic in row and column averages of $\widehat{K}$, while the PRNU is assumed to follow a zero-mean random distribution.
- Artifact suppression by subtracting row and column averages

$$
\begin{aligned}
\widehat{K}[i,j]' &= \widehat{K}[i,j] \\
&\quad - \frac{1}{m}\sum_{i=1}^{m}\widehat{K}[i,j] - \frac{1}{n}\sum_{j=1}^{n}\widehat{K}[i,j] \\
&\quad + \frac{1}{mn}\sum_{i=1,j=i}^{m,n}\widehat{K}[i,j]
\end{aligned}
$$

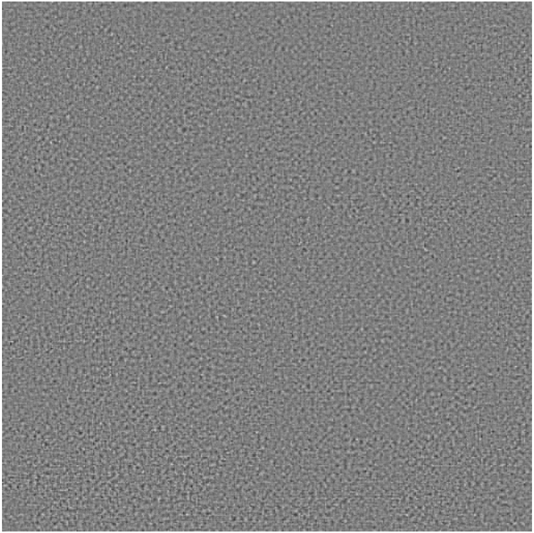
[Goljan, 2008]

Linear Pattern



- $\widehat{K} - \widehat{K}'$ is the linear pattern - used to classify camera model or brand for camera model identification see [Filler and Fridrich, 2008]
- In the presented work, the linear pattern is only a confounding factor, so from now on, $\widehat{K}'$ is our fingerprint.

Fingerprint



Outline

Fingerprint Detection

- Was image **taken with a given camera**?
- Does image noise residual **contain camera fingerprint**?
- noise residual of image I under question: $W = I - F(I)$
- binary **hypothesis test**:

  noise only hypothesis: $W = \Theta$

  fingerprint presence hypothesis: $W = I\widehat{K}' + \Theta$
- Θ denotes pure noise - sequence of **random** variables

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Decision

- **correlate** W of image I with $I\widehat{K}'$
- if $NCC \;\leq\; NCC_{threshold}$: **noise only**
- if $NCC \;>\; NCC_{threshold}$: **fingerprint present**

Outline

Setup

- database with images **sorted by model/camera**
- **split** the files into two sets
  - one for **estimating** fingerprints
  - the other for **evaluation** of detection performance
- randomly pick 50 images for each camera for fingerprint estimation

Determine $NCC_{threshold}$ - Step 1

- 35 cameras, 7 brands, 16 models
- images which were **not used for fingerprint estimation**
- correlate:
  - all images taken with a source camera c_k with the respective source-camera-fingerprint $\widehat{K}'$ ("matches")
  - all images taken by a camera c_i with the fingerprints of cameras c_1, c_2, ... c_{i-1}, c_{i+1}, ... c_k

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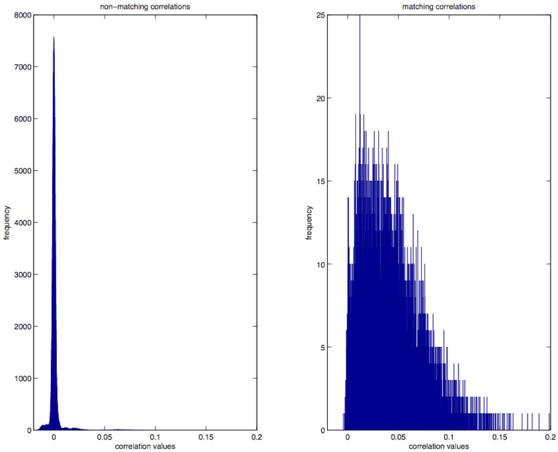
Determine $NCC_{threshold}$ - Step 2

histograms of all correlations of images in database



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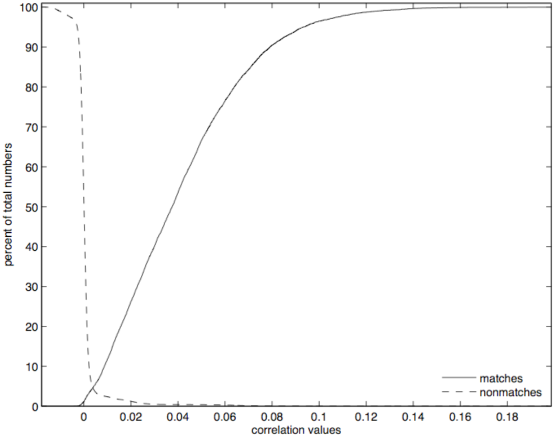
Determine $NCC_{threshold}$ - Step 3

what values are acceptable for false-positives and false-negatives?



Error-Rates

intersection of curves: **Equal Error Rate**
False- **Acceptance**-Rate, i.e. False-**Positive**-Rate
False-**Rejection**-Rate, i.e. False-**Negative**-Rate

Accuracy of estimated EER/threshold

compute **confidence intervals**

1. randomly draw n samples out of n correlation coefficients separately for matching and non-matching coefficients
2. calculate EER and threshold
3. repeat step 1 and 2 a 1000 times

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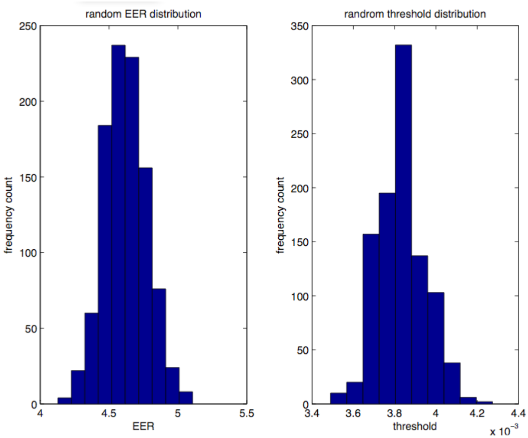
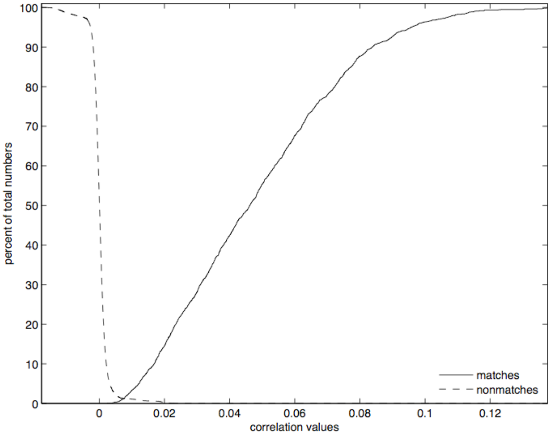


the lower and upper bound including 95% of the values represent the ”confidence-interval”

smaller confidence intervals $\Longleftrightarrow$ better accuracy

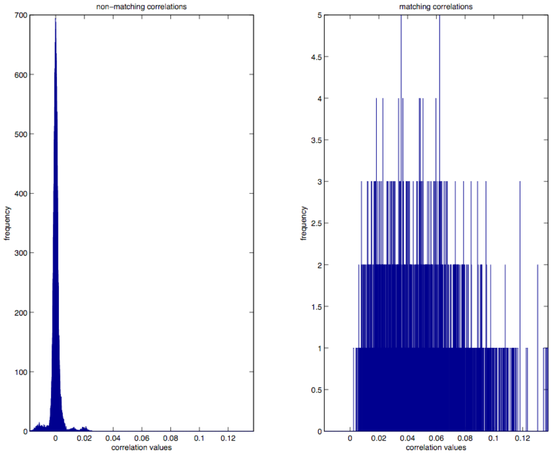
$NCC_{threshold}$ - selected image set

decrease EER and increase threshold interval by choosing images/cameras with per-camera EER of < 1



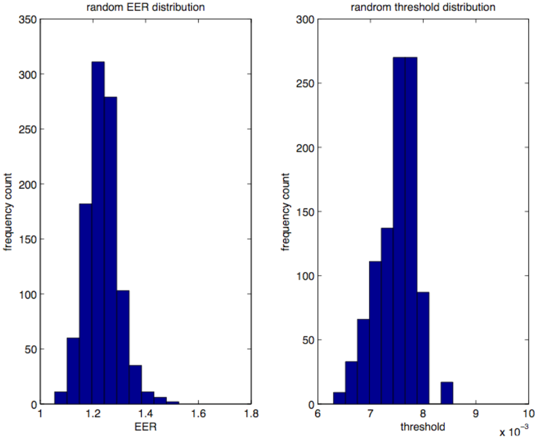
$NCC_{threshold}$ - selected image set

histograms of correlation values of images/cameras with per-camera EER of < 1



$NCC_{threshold}$ - selected image set

resulting confidence interval by choosing images/cameras with per-camera EER of < 1



$NCC_{threshold}$ - values for selected image set

EER	EER-CI	threshold	threshold-CI
1.22	1.14 -1.34	0.0075	0.0068 - 0.0079

EER: equal error rate; CI: confidence interval;

Several variants...

- One problem with our input data was different resolutions.
  $\Rightarrow$ Work on 512^2 pixel segments.
  - **one** segment per corner
  - **6 segments** in each corner (3 horizontal - 2 vertical) for total of 24 segments of 512^2 pixels
- **different wavelet** (db4 instead of db8)
- **different noise filter**

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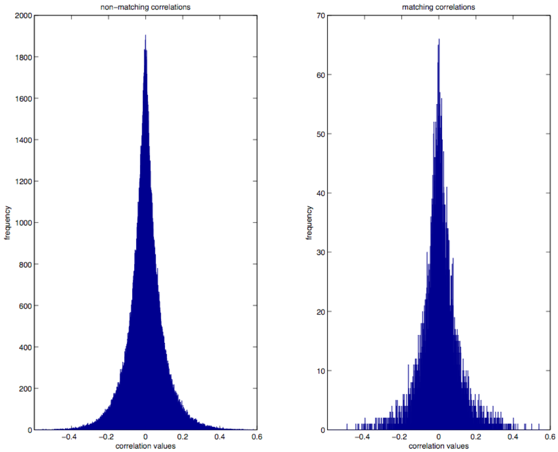
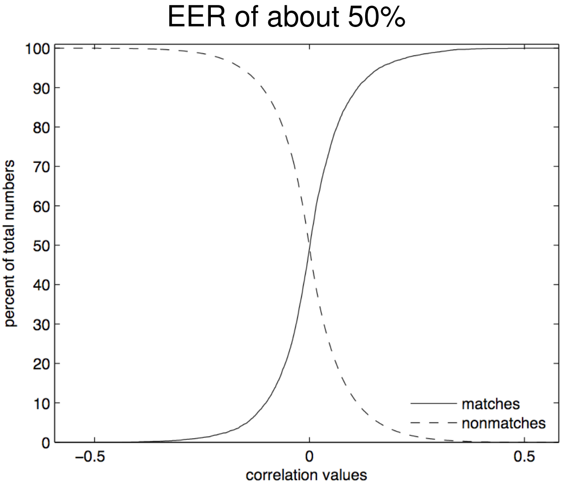
$NCC_{threshold}$ - using Wiener filter

histograms of correlation values by using a Wiener filter



$NCC_{threshold}$ - using Wiener filter



Discussion

- PRNU seems **practicable** for several application scenarios
- **Quality of images** to estimate the PRNU has considerable impact on the achievable error-rates
- Determining a threshold depends on **application scenario**

- Outlook
  - PRNU should be estimated **for each color channel separately**
  - consider eventual **transformations** on images before matching to fingerprint
  - e.g. [Fridrich, 2009] strongly advocates to use **Peak to Correlation Energy** measure (PCE) instead of NCC
  - (still) other **block-sizes** / **block-locations** could be considered
  - other **filters** could be used

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Thank you for your attention.

Questions?