



SOURCE CAMERA MODEL IDENTIFICATION BASED MACHINE LEARNING APPROACH

PhD student

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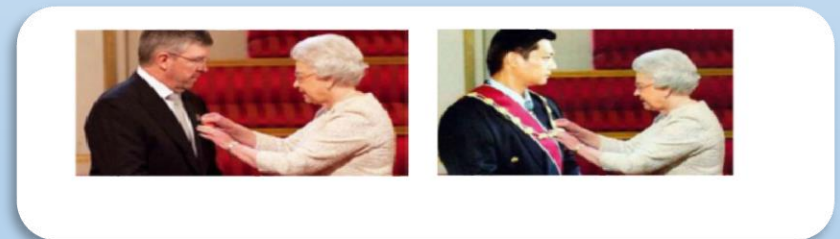
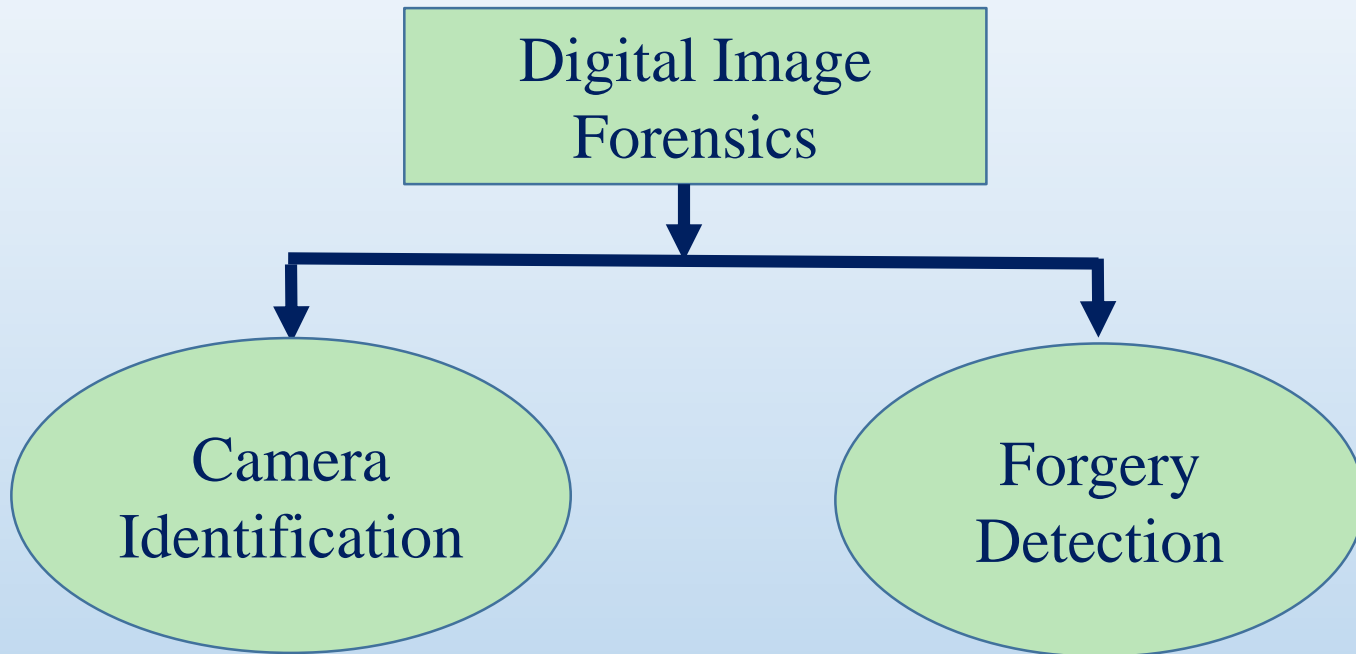
Supervised by

MARC CHAUMONT FRÉDÉRIC COMBY

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DIGITAL IMAGE FORENSICS



a-Original image b-Tampered image

Why Source Identification?

- In tracing the history of an image, identifying the device used for its acquisition.
- In a court of law, the origin of a particular image can represent crucial evidence.



Brand, Model, Device

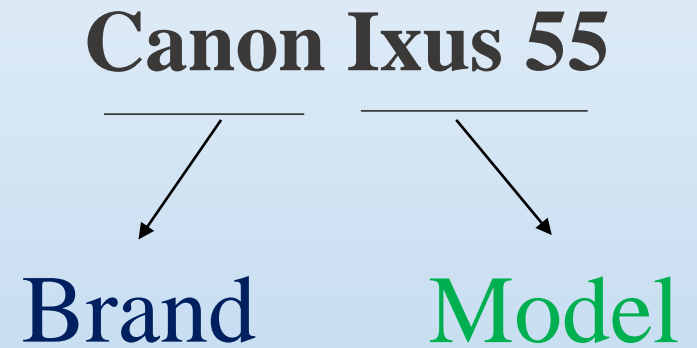
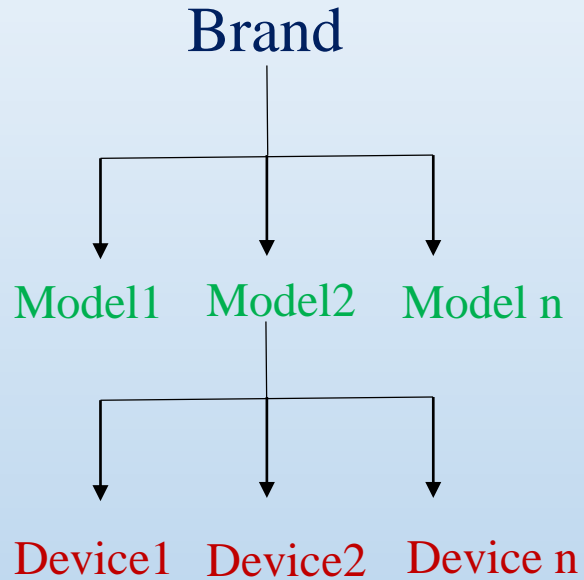
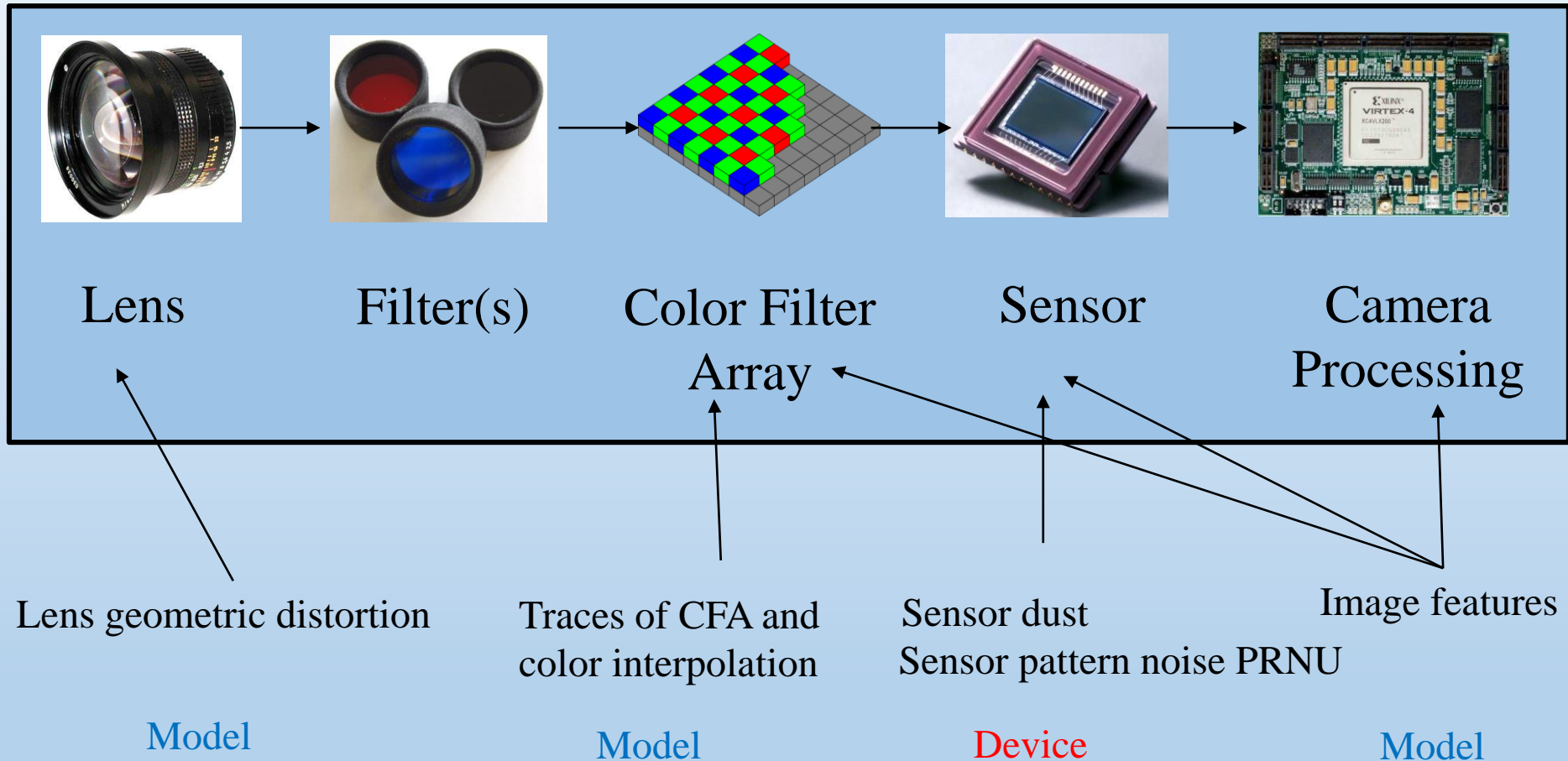


Image Acquisition Pipeline



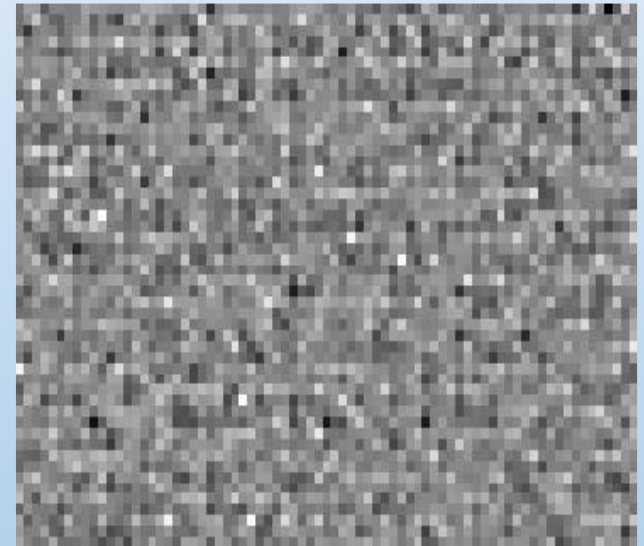
Methods Based Correlations

- **PRNU** Photo Response Non Uniformity is a major source of pattern noise.
- It is a reliable method for identifying individual source camera **device** because it is unique for each sensor [3].

$$N = I - F(I)$$

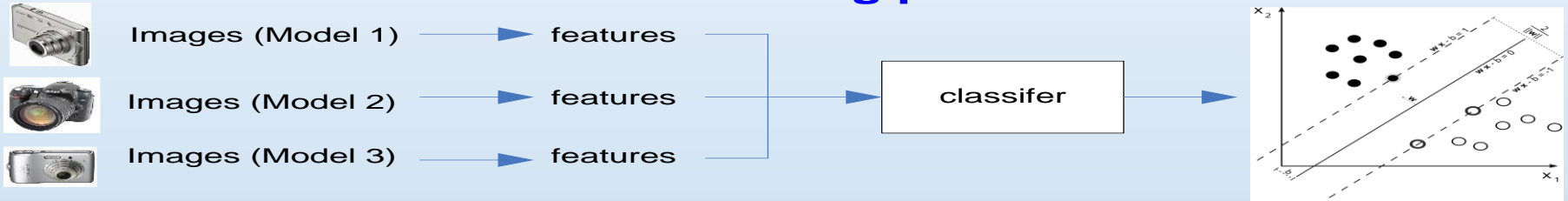
$$K_c = \frac{\sum NI}{\sum I^2}$$

$$\rho(N, K_c) = \frac{(N - \bar{N}) \cdot (K_c - \bar{K}_c)}{\|N - \bar{N}\| \cdot \|K_c - \bar{K}_c\|}$$

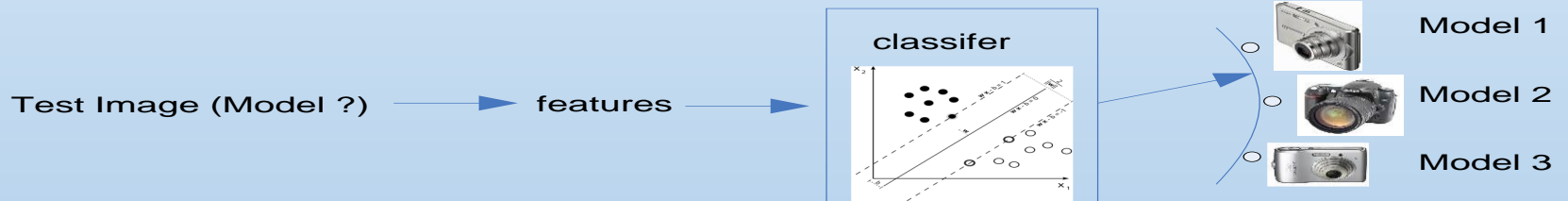


Proposed Method

training procedure



testing procedure



Proposed Method

➤ Principle:

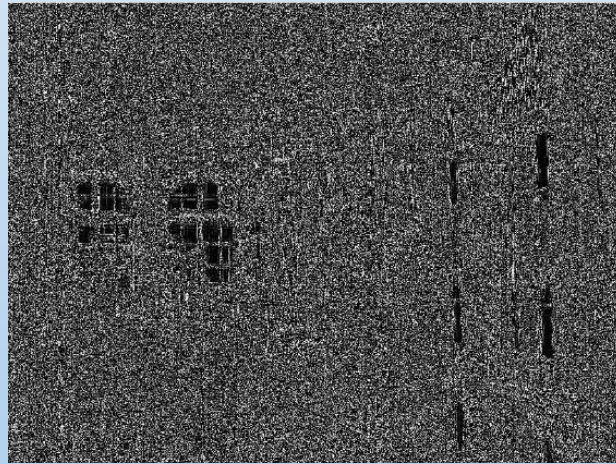
- Extract a polluted sensor noise POL-PRNU.
- Extract Two sets of features from POL-PRNU.

POL-PRNU Extraction

- POL-PRNU polluted sensor noise is the sensor noise contaminated with other types of noise like image contents[3]:

$$N = I - F(I),$$

where I is the image, $F(I)$ is a wavelet based denoising filter.



Fig(1) Sample image with its residual noise

Feature set (1)

High order statistics from POL-PRNU

- High order statistic features among neighboring pixels from the POL-PRNU[4] .

$$\mathbf{R} \leftarrow \text{trunc}_T(\text{round}(\mathbf{L}/q)),$$

where trunc_T minimizes the residual range with $T \in \{-T, \dots, T\}$, $\text{round}(x)$ gives nearest integer value of x , \mathbf{L} is the linear pattern of POL-PRNU, $q \in \{1, 1.5, 2\}$.

- The horizontal and vertical co-occurrences matrix \mathbf{C} is given by:

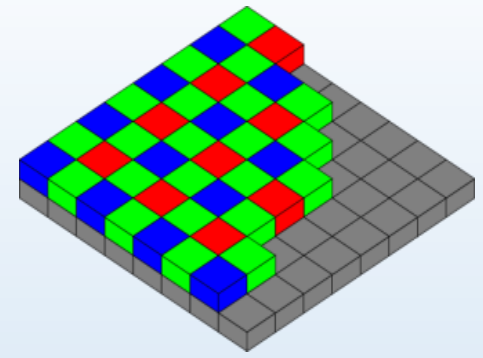
$$\mathbf{C}_d^h = \frac{1}{Z} \left| \{ (i,j) \mid \mathbf{R}_{i,j} = d1, \mathbf{R}_{i,j+1} = d2, \mathbf{R}_{i,j+2} = d3, \mathbf{R}_{i,j+3} = d4 \} \right|,$$

where Z is the normalization factor, $\mathbf{R}_{i,j} \in \mathbb{N}$, $d = (d1, \dots, d4) \in \{-T, \dots, T\}^4$ with $T=2$. Equivalently we can compute the vertical co-occurrences matrix.

- This step gives 10764 Features

Feature set (2)

Traces of color dependencies in CFA interpolation



- The CFA & interpolation introduces specific correlations between the samples of a color image. Bayer array is the most frequently used.
- Compute the normalized cross correlation between the combination of the POL-PRNU of the color channels $\{C1, C2\} \in \{RR, GG, BB, RG, RB, GB\}$ and their shifts $\Delta 1 \in \{0, \dots, 3\}, \Delta 2 \in \{0, \dots, 3\}$ [5]:
- This step gives 96 features.

$$\rho(C1, C2, \Delta) = \frac{\sum_{i,j} (C1_{i,j} - \overline{C1})(C2_{i-\Delta 1, j-\Delta 2} - \overline{C2})}{\sqrt{\sum_{i,j} (C1_{i,j} - \overline{C1})^2 \sum_{i,j} (C2_{i-\Delta 1, j-\Delta 2} - \overline{C2})^2}}$$

Experiments & Results

- We used 14 camera model from Dresden database[6].
- We used 1400 images for training, 100 images for each camera model.
- We used 1400 images for testing, 100 images for each camera model.
- We have $(10764 + 96 = 10860)$ features.
- SVM classifier with radial basis function (RBF): $K(x_i, x_j) = e^{-\gamma |x_i - x_j|^2}$, $\gamma > 0$.
- Apply grid search and cross-validation to choose the best parameters c and γ .
- Use best parameters c and γ to train and test SVM [7].

Experiments & Results

Total Classification Accuracy **97.81 %**

CAMERA MODEL	Agfa Photo DC-733s	Agfa Photo DC-830i	Agfa Photo Sensor 530s	Canon Ixus 55	Fujifilm FinePix J50	Kodak M1063	Nikon D200 Lens A/B	Olympus M1050SW	Panasonic DMC-FZ50	Praktica DCZ 5.9	Samsung L74wide	Samsung NV15	Sony DSC-H50	Sony DSC-W170
CLASSIFICATION ACCURACY (%)	96.93	97.92	98.78	99.57	98.35	98.21	99.07	98.92	99	97.97	99.91	97.57	93	93.94

Table 1. Identification accuracies for the fourteen camera models

Method	Total Accuracy
CFA	86.93
CO-OCCURRENCES	96.91
FILLER et al. [5]	88.23
PROPOSED METHOD (CFA+CO-OCCUR)	97.81

Table 2. Comparison of the proposed method with other approaches.

Conclusions

- Source Camera Identification is the process of deciding which camera has been used to capture a particular image.
- Our method identifies camera **model** based machine learning approach.
- The results illustrate the efficiency of the proposed method since it provides 97.81% of accuracy compared to Filler's method 88.23%.

Perspectives and Future plan

- Enhance the proposed method by extracting more features increase the accuracy.
- Try a bigger database with more camera models.
- Test the data set with deep learning approach and CNN.

References

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- [5] Filler T., Fridrich J., Goljan M.,”Using sensor pattern noise for camera model identification”, 2008.
- [6] Thomas Gloe, Rainer Böhme, ‘The Dresden Image Database for Benchmarking Digital Image Forensics’ SAC’10 March 22-26, 2010, Sierre, Switzerland.
- [7] Chih-Chung Chang and Chih Jen Lin <http://www.csie.ntu.edu.tw/~cjlin/libsvm>

THANK YOU

Questions?