A Machine Learning Approach to Approximate the Age of a Digital Image

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Outline

Image Age Approximation

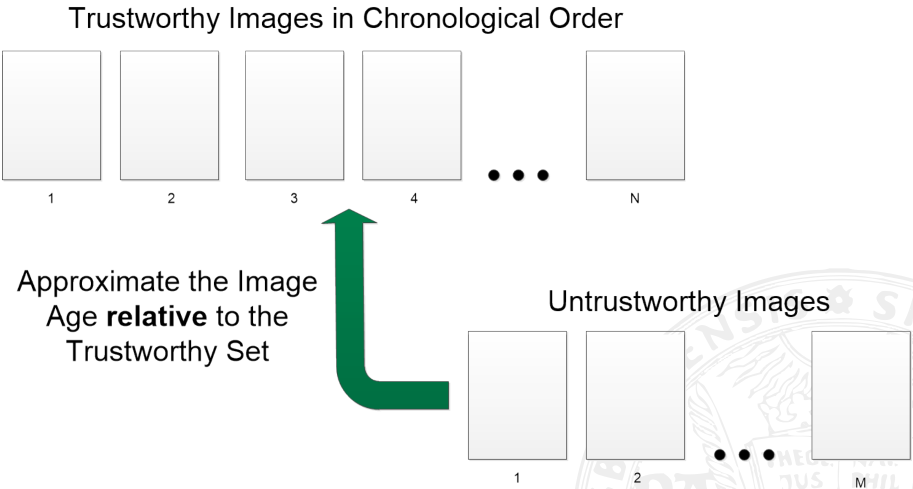

Figure: Overview image age approximation.

Image Age Approximation

- Image age approximation is relevant to forensic analysts when the chronological order among pieces of evidence can help to deduce a causal relationship between events.
- The time information from the EXIF header is usually not trustworthy.

  $\Rightarrow$ Reliable Methods to approximate the image age are required!!

In-Field Sensor Defects

In-field sensor defects:

- Develop after the manufacturing process and accumulate over time.
- Are due to cosmic radiation [1].
- Spread to the neighboring pixels because of preprocessing (e.g. demosaicing).

The trend towards ISO expansion and smaller pixel sizes increases the defect development rate [2].

Defect model,

$$f(I) = I + IK + \tau D + c + \Xi. \tag{1}$$

Figure: In-field sensor defects extracted from captured dark-field images.

Defect Examples

Figure: In-field sensor defects in a regular scene image.

Defect Examples

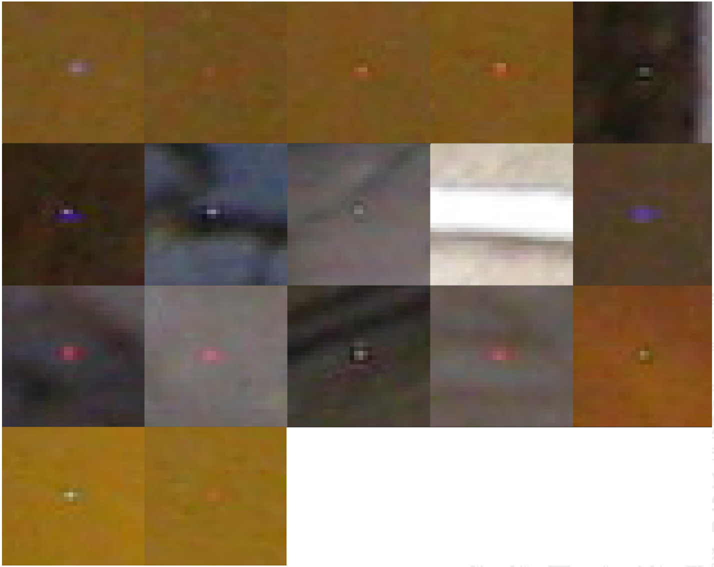

Figure: In-field sensor defects in a regular scene image.

Fridrich et al. propose a maximum likelihood approach in [3], where:

- A defect is considered being noise, and by applying a denoising filter (i.e. a median filter) the defect is filtered out.
- The main assumption is, that the differences between the median filter residual and the sum of the defect parameters (K, D, c) follow a normal distribution, i.e. $N_{(0,\sigma^2)}$.
- The parameter K, D, c, σ^2 are estimated with a maximum likelihood approach as well.
- The age of an image is approximated by

$$\hat{j} = \operatorname*{argmax}_{j} \prod_{i \in \Omega} \frac{1}{\sqrt{2\pi}\hat{\sigma}_{(i)}^{(\Psi)}} \exp \frac{W_{(i)} - \left(I_{(i)} K_{(i)}^{(\Psi)} + \tau D_{(i)}^{(\Psi)} + c_{(i)}^{(\Psi)} \right)}{2\hat{\sigma}_{(i)}^{2(\Psi)}}. \tag{2}$$

In contrast to [3], we consider image age approximation as a multi-class classification problem.

- A class is defined by the time interval between two consecutive defect onsets.

⇒ We propose to utilize traditional machine learning techniques i.e.

Naive Bayes Classifier (NB)

Support Vector Machine (SVM)

Features

- Spatial defect property: single peak in the middle of a smooth image area.
- Median filter smooths out such a peak.
  $\Rightarrow$ The median filter residual contains the defect magnitude and is used as classification feature.

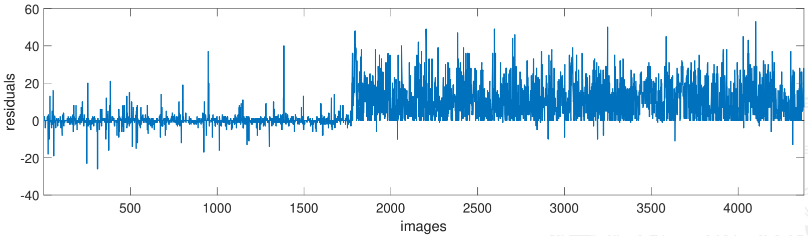

Figure: Residuals of a defective pixel over the set of chronologically ordered images.

With regard to a pixel's dynamic range from 0 to 255 and d defects, 511^d feature combinations fully define the feature space.

Naive Bayes Classifier (NB)

- The features are regarded as d random variables $X = \{X_1, \ldots, X_d\}$ and

$$\hat{y} = \underset{y \in Y}{\operatorname{argmax}} \; P(y|\vec{x}) = \underset{y \in Y}{\operatorname{argmax}} \; P(y) \prod_{i=1}^{d} P(\vec{x}_{(i)}|y). \tag{3}$$

- To estimate the conditional probability $P(\vec{x}_{(i)}|y)$ the conditional probability distribution $p(X_i|\Psi)$ for defect X_i depending the defect's presence (i.e. $\Psi = \psi_1$ if the defect is present and $\Psi = \psi_0$ otherwise) has to be estimated.
- We regard three different estimation techniques:
  - A 'Histogram Estimation' with adaptive smoothing (NB-HE).
  - Assuming $p(X_i|\Psi)$ to be normally distributed (NB-NE).
  - A 'Kernel Density Estimation' (NB-KDE).

Support Vector Machine (SVM)

- The feature space is interpreted as d dimensional hypercube with an edge length of 511 (i.e. $[-256, 256]$).
- Find k mutually exclusive subspaces (one for each class).
- In a one vs. one scenario $\frac{k(k-1)}{2}$ SVMs are trained.
- We used the standard Matlab SVM implementation.

Dataset

- All the experiments rely on images from three different devices:
  - A Nikon E7600 (1768 images).
  - A Canon PowerShot A720IS (4379 images).
  - A Sony DSC-P8 (2302 images).
- All images are JPG compressed 8 bit RGB color files.
- All devices were used as personal cameras to capture regular scene images (e.g. vacation scenes).

Figure: Randomly sampled images from the Nikon, Canon and Sony.

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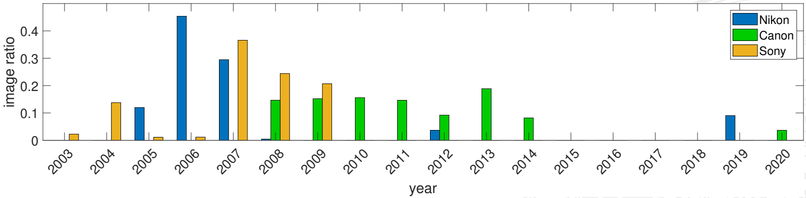

Figure: Relative amount of images per year.

- To approximate the age of an image we regard:
  - 23 defects spreading over 87 pixels from the Nikon.
  - 17 defects spreading over 65 pixels from the Canon.
  - 8 defects spreading over 42 pixels from the Sony.
- These defects define 8, 7 and 7 classes (Nikon, Canon and Sony).

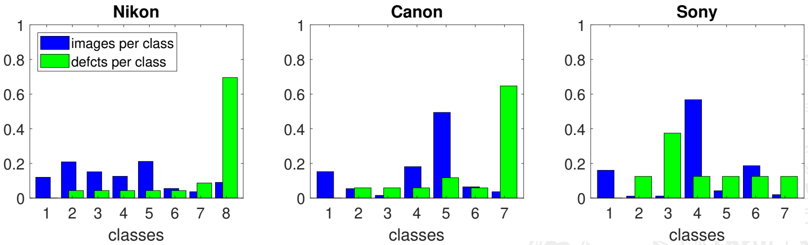

Figure: Relative amount of images and defects per class.

Performance Metrics

- The general classifier performance is evaluated based on the empirical error,

$$L_S(\hat{y}) = \frac{1}{|S|} \sum_{i=1}^{n} I[\hat{y} \neq y]. \tag{4}$$

- To evaluate the prediction performance for a single class we computed the f1-score,

$$\mathrm{f1} = \frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}. \tag{5}$$

Experimental Results

Table: Average empirical error (over 200 runs). The left value shows the empirical error that results when it is assumed that the class probabilities follow the training data distribution, and the right values results when uniform class probabilities are assumed.

Device	**KDc**	**NB-NE**	**NB-HE**	**NB-KDE**	**SVM**
Nikon	0.46	0.46 / 0.47	0.35 / 0.37	0.38 / 0.39	0.38 / 0.38
Canon	0.28	0.27 / 0.31	0.20 / 0.24	0.21 / 0.26	0.19 / 0.22
Sony	0.33	0.28 / 0.34	0.25 / 0.36	0.21 / 0.33	0.21 / 0.30

- The SVM achieves the best results, which are considerably better than the method proposed in [3] (KDc).
- Based on a feature analysis, the estimated probability of a residual being zero after the defect onset is 0.2113, 0.1330 and 0.1847 (Nikon, Canon and Sony).

- The 'NB-HE' and 'NB-KDE' achieve almost the same low error rates.
- The 'Kernel Density Estimation' best generalizes the observed relative residual frequency ⇒ preferred estimation technique.

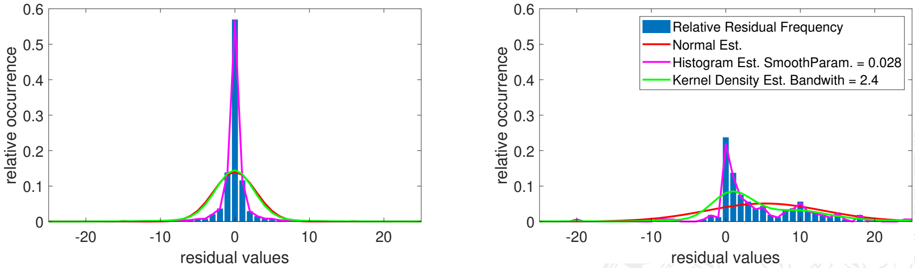

Figure: Illustrates the different probability distribution estimation techniques. The left figure show the relative residual frequencies before the defect onset and the right figure illustrates the relative frequencies afterwards.

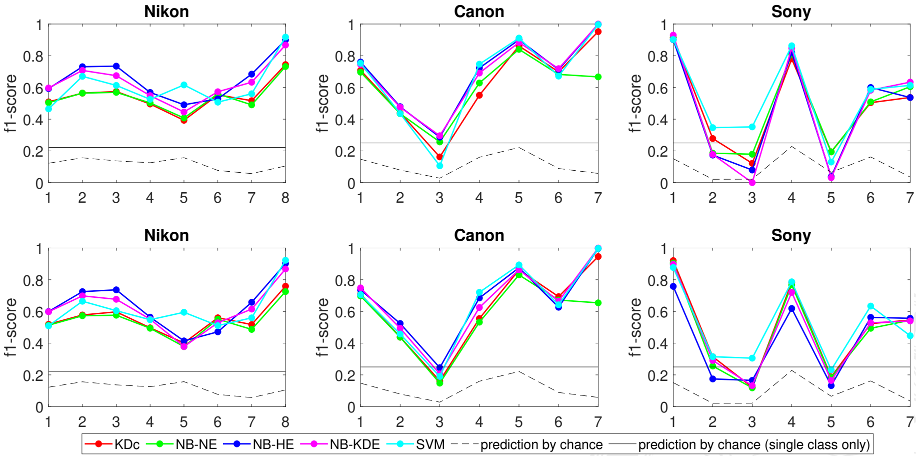

Figure: The average f1-score for each class. The top row represents the f1-score when the class probabilities are assumed to follow the training data distribution, and the bottom row represents the f1-score when uniform class probabilities are assumed.

Conclusion

- Image age approximation based on in-field sensor defects is a multi-class classification problem.
- The described SVM achieves the best results, which are considerably better than the current stat-of-the-art.
- The more images for training and the more defects per class, the better the results.
- In particular, when a class is defined by multiple defects, the accuracy for that class is very high,

  ⇒ an f1-score of 1 and 0.9227 for the last Canon and Nikon class.

References

[1] A. J. Theuwissen, “Influence of terrestrial cosmic rays on the reliability of ccd image sensors part 1: Experiments at room temperature,” *IEEE Transactions on Electron Devices*, vol. 54, no. 12, pp. 3260–3266, 2007.

[2] G. H. Chapman, R. Thomas, R. Thomas, K. J. Coelho, S. Meneses, T. Q. Yang, I. Koren, and Z. Koren, “Increases in hot pixel development rates for small digital pixel sizes,” *Electronic Imaging*, vol. 2016, no. 12, pp. 1–6, 2016.

[3] J. Fridrich and M. Goljan, “Determining approximate age of digital images using sensor defects,” in *Media Watermarking, Security, and Forensics III* (N. D. Memon, J. Dittmann, A. M. Alattar, and E. J. D. III, eds.), vol. 7880, pp. 49 – 59, International Society for Optics and Photonics, SPIE, 2011.

Thank you for your attention!