# Reduced Complexity Image Clustering based on Camera Fingerprints


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## Introduction

- Digital images have brought tremendous changes in human life
  - Documenting news
  - Sharing life events on social media
  - Providing evidence in the court of law
- At the same time, forensic analysis of images faces various problems
  - Source identification
  - Tampering detection
  - Grouping according to a common source
- Unique camera fingerprints can help solving the above mentioned tasks
  - Each acquisition device leaves unique intrinsic traces
  - Photo Response Non Uniformity (PRNU) is the more relevant among them [1][2]
  - PRNU is unique, stable and multiplicative in nature

Figure 1: Camera fingerprint

**Problem**: clustering images according to the source device. The clustering is done without any prior information about

- The source camera
- Number of source cameras
- Number of images captured with an individual camera

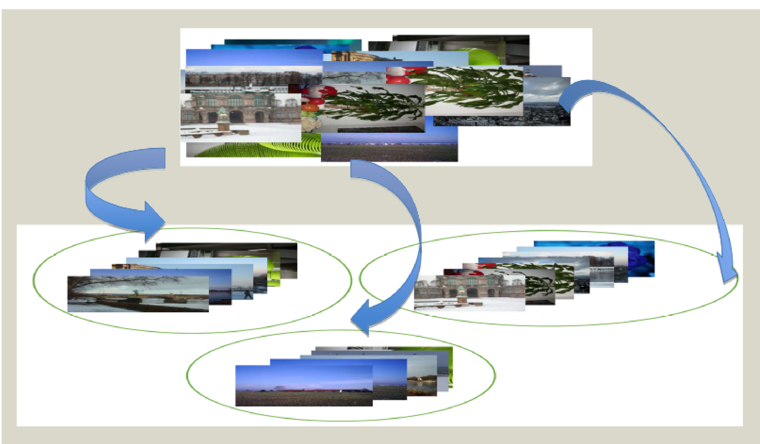

Figure 2: Image clustering.

**Challenges**:

- High I/O and computational costs
- Large memory requirements
- Number of clusters $(NC) \gg$ size of clusters $(SC)$

**Objective**: simple algorithm with reduced complexity

## Basic Concepts

- Estimate and standardize camera fingerprints [1]
  - $M = \{F_i | F_i = \Phi(X_i - D(X_i)), i = 1, \dots n\}$
  - $D(.)$ is the denoising function
  - $\Phi(.)$ normalizes to zero mean unit norm
- Compute NCC between $F_i$ and reference $RF_k$
  - $\rho(i) = \frac{1}{d}\sum_{j=1}^{d} RF_k[j]F_i[j]$
- Compute threshold
  - $T = \sqrt{2/d}\, erfc^{-1}(2 \times PFA)$
  - $PFA$ is the desired probability of false alarm
- If $\rho$ between $F_i$ and $RF_k$ is greater than $T$ then they belong to the same camera

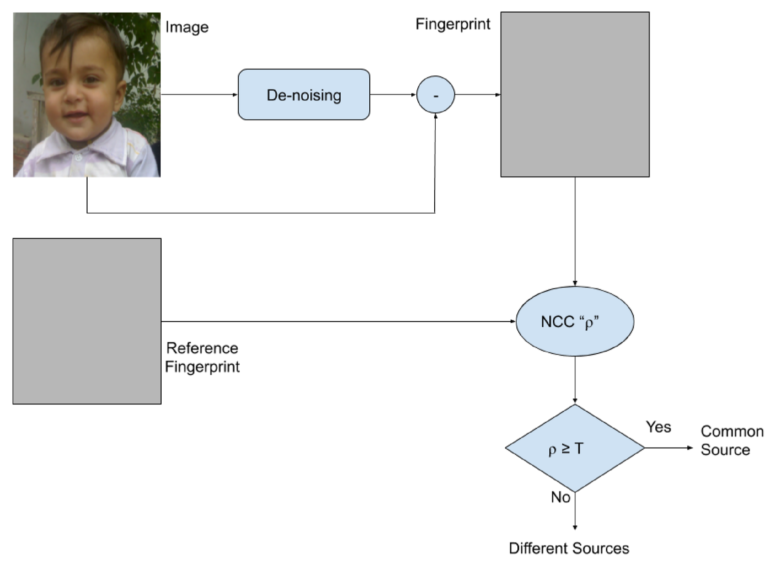


Figure 3: Fingerprint estimation and matching

## RCIC Algorithm

Initialize

- Set of unclustered fingerprints equal to $M$
- $k = 1$

Repeat

- Randomly select one unclustered fingerprint as reference $RF_k$ and assign it to cluster $C_k$
- For each unclustered fingerprint $F_i$
  - Compute NCC $\rho$ between $RF_k$ and $F_i$
  - If $\rho \geq T$, the fingerprint $F_i$ is assigned to cluster $C_k$, otherwise $F_i$ is left unclustered
- $k = k + 1$

Until all fingerprints are assigned to a cluster $C_k$

Attraction stage (optional)

- For each $C_k$ an average reference fingerprint $ARF_k$ is computed by averaging all fingerprint in $C_k$ and normalizing the result to zero mean and unit norm
- $k = 1$

## RCIC Algorithm (Cont...)

Repeat

- Randomly select one non-merged $ARF_i$ as reference $RF_k$
- For each non-merged $ARF_i$
  - Compute NCC $\rho$ between $ARF_i$ and $RF_k$
  - If $\rho \geq T$, merge $ARF_i$ and $RF_k$ clusters, otherwise left $ARF_i$ non-merged
- $k = k + 1$

Until all $ARF_k$ corresponding $C_k$ are either treated as $RF_k$ or merged with some other cluster

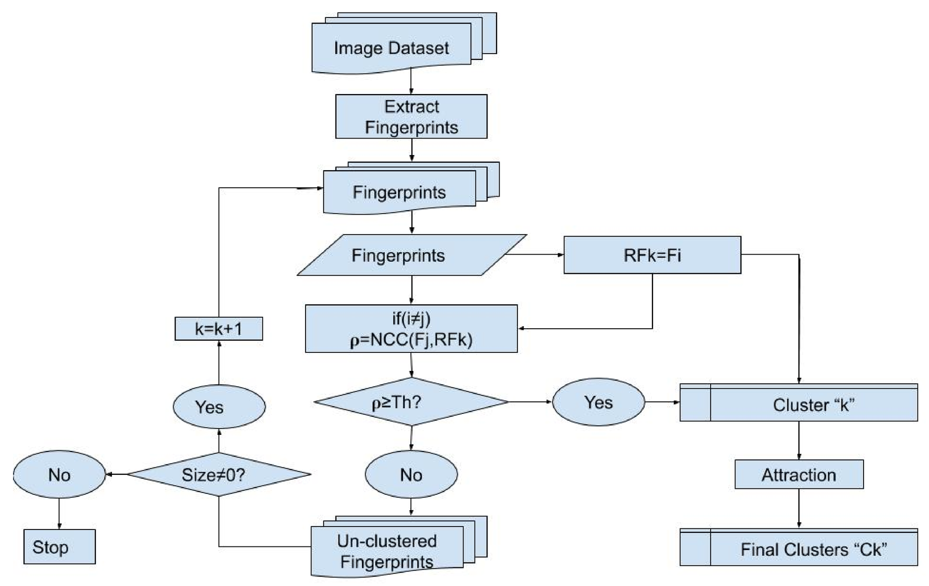


Figure 4: RCIC algorithm

## Experimental Results

Dresden dataset is used for experiments

- D1: $25$ cameras, each contributing $40$ images
- D2: $25$ cameras, with $20$, $30$, $40$, $50$ and $60$ images
- D3: $50$ cameras, each contributing $20$ images
- D4: $50$ cameras, with $10$, $15$, $20$, $25$ and $30$ images
- All the images are center cropped to $1023 \times 1023$

Performance metrics

- $P = \frac{\sum_k (max_j |c_k \cap \omega_j|)}{\sum_k |c_k|} \qquad R = \frac{\sum_j (max_k |c_k \cap \omega_j|)}{\sum_j |\omega_j|}$
  - ground truth classes $\Omega = \{\omega_1, \omega_2, \omega_3, \dots \omega_{NC}\}$
  - generated clusters $C = \{c_1, c_2, c_3, \dots c_y\}$
- $F = 2 \times \frac{(P \times R)}{(P + R)} \qquad cr = \frac{n \times (n-1)}{2 \times t_c}$
- The probability of false alarm $PFA$ is set to $10^{-6}$

Table 1: Variance of evaluation metrics for different No. of experiments

| No. of Exp. | $\sigma^2$(P) | $\sigma^2$(R) | $\sigma^2$(F) |
|---|---|---|---|
| 25 | $1.3 \times 10^{-6}$ | $1.5 \times 10^{-4}$ | $6.0 \times 10^{-5}$ |
| 20 | $2.0 \times 10^{-5}$ | $1.8 \times 10^{-4}$ | $7.5 \times 10^{-5}$ |
| 15 | $1.8 \times 10^{-6}$ | $1.4 \times 10^{-4}$ | $5.1 \times 10^{-5}$ |
| 10 | $4.5 \times 10^{-6}$ | $1.1 \times 10^{-4}$ | $4.2 \times 10^{-5}$ |

## Experimental Results (Cont...)

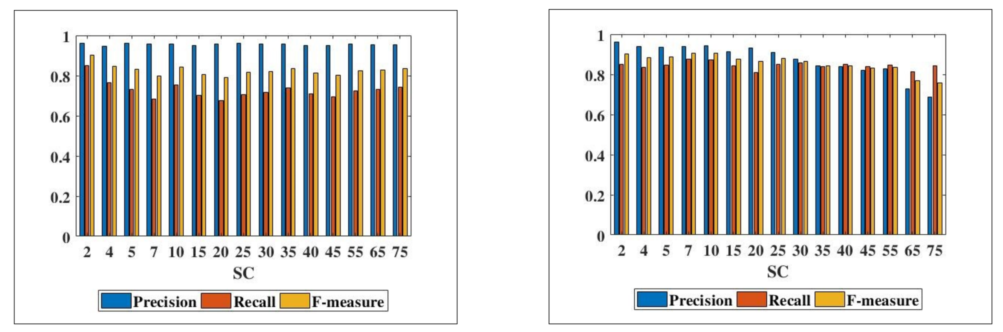

Figure 5: Performance vs increasing $SC$ for $NC = 53$: (left) without attraction, (right) with attraction

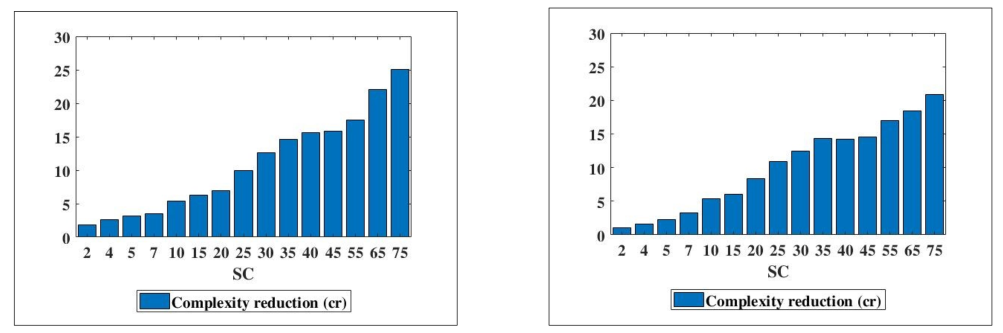

Figure 6: $cr$ vs increasing $SC$ for $NC = 53$: (left) without attraction, (right) with attraction

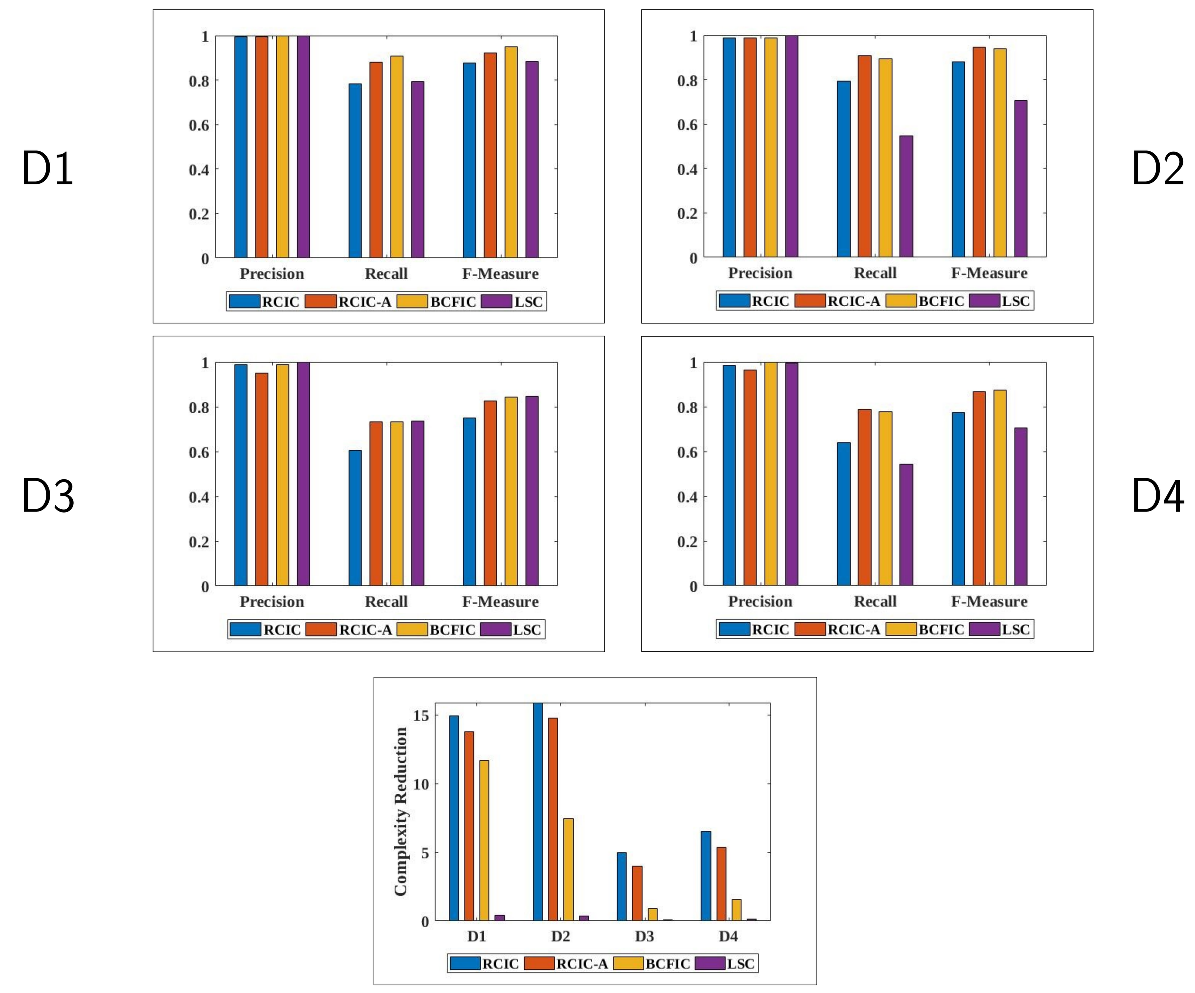


Figure 7: Comparison of RCIC and RCIC-A algorithms with BCFIC [3] and LSC [4] algorithms

## References


[1] M. Chen, J. Fridrich, M. Goljan and J. Lukás, 2008. *Determining image origin and integrity using sensor noise*, IEEE Trans. Inf. Forensics Security, vol. 3, no.1, pp. 74-90.

[2] J. Lukás, J. Fridrich and M. Goljan, 2006. *Digital camera identification from sensor pattern noise*, IEEE Trans. Inf. Forensics Security, vol. 1, no.2, pp. 205-214.

[3] G.J. Bloy, 2008. *Blind camera fingerprinting and image clustering*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 30, no. 3, pp. 532-534.

[4] X. Lin and C. T. Li, 2017. *Large-scale image clustering based on camera fingerprints*, IEEE Trans. Inf. Forensics Security, vol. 12, no. 4, pp. 793-808.