Blind Image Source Camera Identification

K Shimji and M Baburaj

June 4, 2021

Blind Image Source Camera Identification

*

Shimji K
Research scholar
Government Engineering College Kozhikode
Kozhikode, India
shimjik96@gmail.com

Dr. Baburaj M
Assistant Professor
Government Engineering College Kozhikode
Kozhikode, India
baburajmadathil1@gmail.com

***Abstract*—The creation and control of digital images are simplified by computerized preparing apparatuses that are effective and generally accessible. As an outcome, we can at this point don't take the legitimacy of the pictures. This is particularly obvious with regards to legitimate photographic proof. With an ever-increasing computerized crime percentage, the opportunity has already come and gone. This project depicts how digital legal procedures for source examination and identification empower measurable experts to plan a picture under an inquiry to its source camera, in a visually impaired way, with no apriori data about the storage and preparing. Even though Photo Response Non-Uniformity (PRNU) has acquired an incredible interest in image forensics the extraction of camera fingerprint with minimum seen content is still a challenging problem. In our proposed method fingerprint is extracted using a weighted combination of two types of de-noising filters, weighted nuclear norm minimization (WNNM) based filter and wavelet filter. A set of images captured by different mobile cameras at different locations are used as a dataset. Each image is distinct and contains different seen details having varying exposures. After the fingerprint extraction process, the fingerprints are clustered using spectral clustering based on their origin.**

***Index Terms*—Fingerprint, Weighted nuclear norm minimization, Photo response non-uniformity.**

I. Introduction

Digital images are broadly used because of the supply of a large range of adorable digital cameras with different configurations and functionalities. The crudest way to authenticating digital images are by its header [4] or the other associated information. Exchangeable Image File (EXIF) header can contain information about the image like exposure, date, time, etc... But these pieces of data may be lost and even easily modified by image processing tools. There emerge the need of validity of image data. The reliable identification of the device accustomed to acquiring a picture would especially prove useful within the court for establishing the origin of images presented as evidence [10]. The identification method is going to be presented in step with the type of cues they explore. When capturing a digital image multi-processing steps are performed before the storage. Each step is performed in line with a specific camera brand model. This variation may be used to determine the sort of camera from which the image was obtained.

Different types of artifacts are produced in different stages of camera life cycle such as camera manufacturing, image capturing and image processing. These unique traces produced in the images in different stages exist in the images as noise which are unique for each camera. The traces can be formed by de-mosaicing algorithm [12] used in CCD (Charge coupled devices), JPEG (Joint Photographic expert group) compression [6] , Chromatic aberrations produced by lenses [13], Sensor pattern noise produced due to non-uniformity of pixels [2] , sensor dust [1], Dark current non-uniformity [4], etc.

Photo response non-uniformity (PRNU) is a widely accepted camera fingerprint [2]. Jan Lukas [2] introduced PRNU as reference pattern which is unique for camera model. Camera sensor which is the main part of image acquisition is made up of large number of photo detectors. The amount of electrons generated is proportional to the intensity of incident light. Due to the non-homegenity in the physical dimension of detectors the photo response characteristic will also be non-uniform. This is called Photo response non-uniformity (PRNU) [4].This is a manufacturing defect present in sensors and is present in all types of CCD (Charge coupled devices) and CMOS (metal oxide semiconductors) sensors. The blind camera source clustering help us to separate image sources. [3] used row sparsity optimization to suppress the negative effect of outliers produced by Photo Response Non-Uniformity (PRNU).

To identify the source of the image PRNU can be extracted from the image. We can see a lot of papers [15] have worked on this defect to identify camera source. [16] proposed a method to identify source of different videos originated from the same camera after being transmitted by whatsapp in specific. But that method failed to identify the source when different videos originated from same camera. Even though many approaches have done on PRNU and it is widely accepted as finger print of digital camera the extraction of which is still a challenging problem. Numerous de-noising filters [17] has been used for PRNU extraction. A simple algorithm based on low rank matrix approximation [11] exploiting non-local redundancy is used for image de-noising.

There are two types of problems arising. The first question

Identify applicable funding agency here. If none, delete this.

is whether the image under consideration is captured using the camera under question or not. The second question is which images are originated from the same camera device. That is we have to cluster the given images on the basis of their origin without any prior information about the images and the camera device which is used for image acquisition. We can call these types of problem as BCSC (Blind Camera Source Clustering).

II. Imaging Sensor Modeling

In camera source identification method we have an assumption that all all camera sensors are distinct in their photo response. based on this fact we can say that an image is combination of noise content and original image content. In that sense camera sensor out put is a combination of PRNU noise, ideal image content and other noises. The linearized sensor model [4] can be represented as in (1).

$$E = E^{(0)} + E^{(0)} P_{+} Q \tag{1}$$

Where E is the sensor output $E^{(0)}$ is the ideal sensor output, $E^{(0)}$P is the PRNU and finally Q is the sum of all other noises present in the image. our aim is to extract the PRNU which is unique ,non-temporal and random from the image with reduced influence of other constituents.

III. Proposed Methodology

In the proposed work we are using weighted combination of sensor noise obtained using wavelet based de-noising filter and weighted nuclear norm minimization (WNNM) based de-noising filter . Camera PRNU is the noise residual (2). Here I represent the image and $\mathbb{F}(I)$ represent the de-noised image.

$$r = (I - \mathbb{F}(I)) \tag{2}$$

A. PRNU Extraction Using Wavelet Filter

Our implementation of the wavelet based de-noising filter is experimented on the work proposed in [1]. The high-frequency wavelet coefficients of the noisy image are modeled as an additive mixture of a locally stationary i.i.d. signal with zero mean (the noise-free image) and a stationary white Gaussian noise $N(0, \sigma^2)$. The de-noising filter is constructed in two stages. within the first stage, we estimate the local image variance, while within the second stage, the local Wiener filter is employed to get an estimate of the de-noised image in the wavelet domain. From the de-noised image and the original noisy image we obtain the PRNU noise. The steps for finding the denoised image is as follows.

- Using 8-tap Daubachies quadrature mirror filter bank (QMF) calculate the fourth-level wavelet decomposition [2] of the noisy image. The procedure for only the high frequency band only for one fixed level is depicted here.h(i,j), v(i,j) and d(i,j) denote the horizontal, vertical and diagonal sub bands. Where (i,j)ϵJ. J is the index set depends on level of decomposition.
- Using the MAP (maximum a posteriori probability) estimation, measure the local variance of the original noise-free image. This is done for all sub band for 4 sizes of a square W×W neighborhood N, for W∈ 3, 5, 7, 9

$$\sigma_W^2(i,j) = max\left(0, \frac{1}{W^2}\sum_{(i,j)\in N} h^2(i,j) - \sigma_0^2\right)(i,j) \in J \tag{3}$$

- The final estimate si the minimum of the four.

$$\sigma^2(i,j) = min\left(\sigma_3^2(i,j), \sigma_5^2(i,j), \sigma_7^2(i,j), \sigma_9^2(i,j)\right) \tag{4}$$

- Wiener filter is used for obtaining de-noised wavelet coefficients.

$$h_{den}(i,j) = h(i,j)\frac{\sigma^2(i,j)}{\sigma^2(i,j) + \sigma_0^2} \tag{5}$$

  This is repeated for vertical, horizontal and diagonal sub bands.
- Above three steps are repeated for all the four levels and each color channel. By taking the inverse of wavelet transform the de-noised image is obtained.

The estimated fingerprint is a combination of two components: the reference pattern (RP) and the linear pattern (LP). Where a linear pattern is common to cameras that come under the same model but the reference pattern is unique for each camera. A reference pattern is a combination of all types of noises formed by different artifacts introduced by Jpeg compression, Color filter array interpolation (CFA), Sensor noise, etc Two steps in noise residual filtering are necessary inorder to remove inherently embedded signals common to cameras of the same model. This is done using zero-mean operator [2] which maps any member of the image I into zero vector in a de-noised image. The second step realized by Wiener filtering substantially removes JPEG and other periodic artifacts by suppressing peaks in the Fourier domain.

B. PRNU extraction Using WNNM

This method is an expansion of image de-noising using nuclear norm minimization technique. [10]It is shown that low rank matrices are easily recovered. Therefor using soft thresholding [10] in The noisy image can be converted into a low rank matrix(4). This thresholding (4) shrinks larger singular values less and smaller singular values more because weights are inversely proportional to singular values. Since the singular values represent the energy of the major components this non-uniform weighting (4) will enhance the de-noising.

$$S_w(\Sigma)_{ii} = Max(\Sigma_{ii} - w, 0) \tag{6}$$

There are three combinations of an order of the weights and de-noising approach. For a noisy image, singular values are in non-ascending order hence weights are in non-descending order. Because of the non-descending nature of weights WNNM method can bring about a deliberate settled point through iterative regularization [9]

Let y=x+r represent noisy image patch where x is the de-noised patch and r represent additive Gaussian noise with zero mean and variance σ_n^2. our aim is to estimate de-noised patch x from noisy patch y. First create similar patch groups

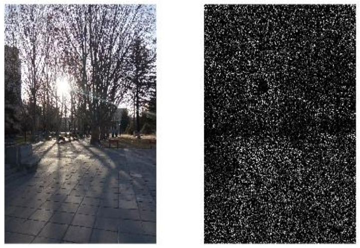

Fig. 1. a)Image captured using iphone6 b) PRNU noise

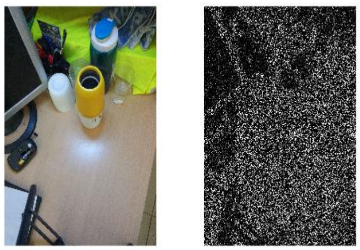

Fig. 2. a)Image captured using GioneeS55 b) PRNU noise

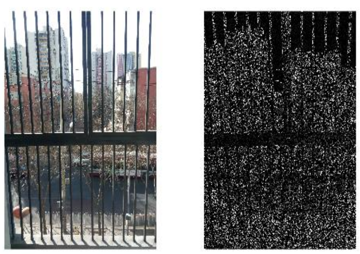

Fig. 3. a)Image captured using Huawei-RY6b) PRNU noise

Fig. 4. Images captured using different mobile cameras and their corresponding PRNU extracted using wavelet filter based method

using k-means [18] clustering technique. Now find the weight corresponding singular values.

$$W_i = c\sqrt{n}/\sigma_i(X_j) + \epsilon \quad (7)$$

$\sigma_i(X_j)$ is the i^th singular value of j^th de-noised patch where c = 0.01, $\epsilon = 2.5$ and n is the number of similar patches in Y_j

Since initially the singular values are unknown the initial $\sigma_i(X_j)$ can be estimated using following equation [**?**]

$$\hat{\sigma}_i(X_j) = \sqrt{max(\sigma_i^2(Y_j) - n\sigma_n^2, 0)} \quad (8)$$

Algorithm for WNNM de-noising

Input: Noisy image
Initialize : $\hat{x}^{(0)}$=y, $\hat{y}^{(0)}$=y
for k=1:K do
Iterative regularization $\hat{y}^{(k)}$=$\hat{x}^{(k-1)} + \delta(y - \hat{y}^{(k-1)})$
for each patch y_j in $y^{(k)}$ **do**
  Find similar patch group Y_j
  estimate weight vector w
  Singular value decomposition [U,Σ,V]=SVD(Y_j)
  Get the estimation $\hat{X}_j = US_wV^T$
end for
Aggregate X_j to form the clean image $\hat{x}^k$
end for Clean image $\hat{x}^{(k)}$

Fig. 5. a)Image captured using iphone6 b) PRNU noise

Fig. 6. a)Image captured using GioneeS55 b) PRNU noise

Fig. 7. a)Image captured using Huawei-RY6 b) PRNU noise

Fig. 8. Images captured using different mobile cameras and their corresponding PRNU extracted using WNNM method

IV. Spectral Clustering

Spectral clustering is the source identification method. Clustering is a method of partitioning a pool of data [8] into distinctive clusters using similarity. spectral clustering method will cluster a set of distinct images from unknown sources into different clusters that is source clustering. In terms efficiency and speed spectral clustering [19] outperforms other clustering methods [18]. [19] make use of spectrum of similarity matrix. This approach reperesent each data point as vertex and edge is used to denote the similarity between the data points. In this manner spectral clustering treat the whole data set as a unified graph. Different similarity measures [19] can be used to determine the similarity between data points. The technique involves representing the data in a low dimension. In the low dimension, clusters in the data are more widely separated, enabling us to use algorithms such as k-means clustering.

V. Results

We have tested 483 images from 18 different cameras which include cameras from same model and different model. Theere is no noticable variation in clustering accuracy for images from same camera model when compared to images from different camera model. When experiment is conducted using only the wavelet based de-noising method the accuracy was 58%. The accuracy was 67.82% when experimented using WNNM method. When the fingerprints from wavelet based de-noising and WNNM based denoising are combined clustering accuracy is increased to 76.4706%.

TABLE I
Performance table

dataset	**Evaluation Measures**		
	Accuracy	***Cluster Purity***	***Miss classification rate***
dataset1	76.89	0.789	16.98
dataset2	76.4706	0.7647	17.3913
dataset3	73.53	0.74.51	26.7361

a

VI. Conclusion

We have investigated the problem of source identification in a unsupervised manner. We used a combination of de-noising filters to extract the features for improving the data content. By varying the contribution of filters by using weight the best result was obtained when given equal weightage. Spectral clustering frame is used along with feature extraction to solve the problem. The accuracy of the combination of features is more when compared with individual features.

References

[1] Chowdhury, Debbrota Paul and Bakshi, Sambit and Sa, Pankaj Kumar and Majhi, Banshidhar, ”Wavelet energy feature based source camera identification for ear biometric images” 2020, pp.139–147.

[2] Lukas, Jan and Fridrich, Jessica and Goljan, Miroslav, ”Digital camera identification from sensor pattern noise”, 2006, pp.205–214

[3] Jiang, Xiang and Wei, ShiKui and Liu, Ting and Zhao, Ruizhen and Zhao, Yao and Huang, Heng, ”Blind Image Clustering for Camera Source Identification via Row-Sparsity Optimization”, 2020.

[4] Kiegaing Kouokam, Emmanuel and Dirik, Ahmet Emir, ”PRNU-Based Source Device Attribution for YouTube Videos”,2019,pp.arXiv–1903

[5] S.Bayram and H.Sencar and N. Memon and I.Avcibas, ”Source camera identification based on CFA interpolation, year”,2005, pp.III-69.

[6] San Choi, Kai and Lam, Edmund Y and Wong, Kenneth KY,”Source camera identification by JPEG compression statistics for image forensics”, 2006, pp.1-4.

[7] Phan, Quoc-Tin and Boato, Giulia and De Natale, Francesco GB, ”Accurate and scalable image clustering based on sparse representation of camera fingerprint”, 1902–1916, pp.7.

[8] Von Luxburg, Ulrike, ”A tutorial on spectral clustering”, 2007, pp.395-416.

[9] S. Gu, L. Zhang, W. Zuo and X. Feng, ”Weighted Nuclear Norm Minimization with Application to Image Denoising,” 2014 IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 2862-2869, doi: 10.1109/CVPR.2014.366.

[10] Tiwari, Mayank, and Bhupendra Gupta. ”Enhancing source camera identification using weighted nuclear norm minimization de-noising filter.”, 2019. 281-288.

[11] Q. Guo, C. Zhang, Y. Zhang and H. Liu, ”An Efficient SVD-Based Method for Image Denoising,” in IEEE Transactions on Circuits and Systems for Video Technology, vol. 26, no. 5, pp. 868-880, May 2016, doi: 10.1109/TCSVT.2015.2416631.

[12] H. Cao and A. C. Kot, ”Mobile camera identification using demosaicing features,” Proceedings of 2010 IEEE International Symposium on Circuits and Systems, 2010, pp. 1683-1686, doi: 10.1109/ISCAS.2010.5537502.

[13] P. -P. Sun, Q. Xue and B. Liu, ”Analysis and Compensation of Color Chromatic Aberration,” 2019 8th International Symposium on Next Generation Electronics (ISNE), 2019, pp. 1-4, doi: 10.1109/ISNE.2019.8896615.

[14] A. E. Dirik, H. T. Sencar and N. Memon, ”Digital Single Lens Reflex Camera Identification From Traces of Sensor Dust,” in IEEE Transactions on Information Forensics and Security, vol. 3, no. 3, pp. 539-552, Sept. 2008, doi: 10.1109/TIFS.2008.926987.

[15] T. Van Lanh, K. Chong, S. Emmanuel and M. S. Kankanhalli, ”A Survey on Digital Camera Image Forensic Methods,” 2007 IEEE International Conference on Multimedia and Expo, 2007, pp. 16-19, doi: 10.1109/ICME.2007.4284575.

[16] R. Rouhi, F. Bertini, D. Montesi and C. Li, ”Social Network Forensics through Smartphones and Shared Images,” 2019 7th International Workshop on Biometrics and Forensics (IWBF), 2019, pp. 1-6, doi: 10.1109/IWBF.2019.8739237.

[17] B. B. Ahamed, D. Yuvaraj and S. S. Priya, ”Image Denoising With Linear and Non-linear Filters,” 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), 2019, pp. 806-810, doi: 10.1109/ICCIKE47802.2019.9004429.

[18] H. Zhang, C. Liu, M. Zhang and R. Zhu, ”A hot spot clustering method based on improved kmeans algorithm,” 2017 14th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), 2017, pp. 32-35, doi: 10.1109/ICCWAMTIP.2017.8301443.

[19] B. Chen, Y. Wang, Fan-Ying Gong, X. Wang and C. Yang, ”A spectral clustering algorithm for automatically determining clusters number,” Proceeding of the 11th World Congress on Intelligent Control and Automation, 2014, pp. 3723-3728, doi: 10.1109/WCICA.2014.7053336.