SOURCE CAMERA DEVICE IDENTIFICATION BASED ON RAW IMAGES

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ABSTRACT

This paper investigates the problem of identifying the source imaging device of the same model for a natural raw image. The approach is based on the Poissonian-Gaussian noise model which can accurately describe the distribution of the given image. This model relies on two parameters considered as unique fingerprint to identify source cameras of the same model. The identification is cast in the framework of hypothesis testing theory. In an ideal context where all model parameters are perfectly known, the Likelihood Ratio Test (LRT) is presented and its performance is theoretically established. The statistical performance of LRT serves as an upper bound of the detection power. For a practice use, when the image parameters are unknown and camera parameters are known, a detector based on estimation of those parameters is designed. Numerical results on simulated data and real natural raw images highlight the relevance of our proposed approach.

***Index Terms*—** Hypothesis testing theory, Source camera identification, Poissonian-Gaussian noise model

1. INTRODUCTION

In today's digital world, due to the popularity of digital cameras and the ease of imaging editing, image forensics has received great focus in the past decade. Digital image forensics can be categorized into two kinds. The one is digital watermarking which is defined as an active forensic approach; the other is defined as a passive forensic approach which discusses the origin or authenticity of the given image. In this paper, we mainly focus on the image origin identification problem.

1.1. State of the art

Source camera or image origin identification, which relies on the camera fingerprints left in the digital images, aims to verify whether a given digital image was acquired by a specific device or a certain camera model.

Source camera identification can generally be divided into two categories [1]. The methodologies in the first category rely on the imaging pipeline. By using the white balancing as a camera fingerprint, the algorithm proposed in [2] identified the device originality of a given image. By exploiting the fingerprints in the acquisition stage such as lens distortion/aberration [3], the method was proposed to identify the source camera model. The methodologies proposed by [4–7] made use of Color Filter Array (CFA) and demosaicing algorithms to authenticate the camera model. The methods in the second category aims to identify the fingerprints of the acquisition

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device. Due to imperfections during manufacturing process, Sensor Pattern Noise (SPN) extracted from given images was used for identifying source camera model [8]. Moreover, the Photo-Response Non-Uniformity noise (PRNU) based detector proposed in [9, 10] could implement device identification. The challenging problems are that a few manufacturer share similar image processing technique which leads to the similarity when extracting fingerprints from given images, especially in the case of same camera manufacturer and model. Otherwise, detectors proposed in the literature limitedly investigate the hypothesis theory and statistical image models.

1.2. Contribution of the paper

In our prior study, based on the hypothesis testing theory with a statistical noise model of a natural image [11], the detector was designed to identify the camera model of a given image [1, 12]. However, this detector can not identify the source camera device of the same model. Inspired by the detector proposed in [1], it is propsoed to identify the unique fingerprint which can not only authenticate the images from different models, but also from different devices of the same model. The main contribution is two folds. The use of the noise model [11], together with hypothesis theory, allows us to optimize the Likelihood Ratio Test (LRT) when camera and image parameters are known. Then in the practical case of not knowing image parameters, estimations have to be used instead; this leads to the design of the proposed detector with estimated parameters. Numerical results show the sharpness of the theoretically established results and the good performance that the proposed statistical test achieves.

1.3. Organization of the paper

The paper is organized as followed. Section 2 recalls the principal of the noise model proposed in [11]. Then, the camera fingerprint is discussed. In Section 3, based on the proposed model, the LRT for camera device detection is proposed and its performance is given. Section 4 addresses the practical detector with estimated image parameters. Finally, Section 5 presents numerical results of the proposed detector on the simulated and real images and Section 6 concludes this paper.

2. POISSONIAN-GAUSSIAN NOISE MODEL

On the assumption of Poissonian-Gaussian noise model which characterizes the response of a digital imaging sensor for a natural raw image [11], the noise model parameters denote a fingerprint remaining the same in an image (see details in [1]). However, the fingerprint proposed in [1] is incapable of identifying the origin of different devices for the same camera model.

By challenging the assumption that among a single image all the pixels from different level sets share the same camera parameters, it is proposed that the pixels of each level set follow the Poissonian-Gaussian noise model with different parameters. Then let us assume that a natural raw image is a vector $\mathbf{Z} = \{z_i\}$ of I pixels where $i \in \{1, \cdots, I\}$. Let us define the fingerprint of camera source device as $(\mathbf{a}, b)$, where the vector $\mathbf{a} = \{a_1, \cdots, a_K\}$, the constant b and the index $k \in \{1, \cdots, K\}$ with K the number of level sets. Hence the following model is proposed:

$$z_i \sim \mathcal{N}(\mu_i, a_k \mu_i + b) \qquad (1)$$

where $\mathcal{N}(\cdot)$ denotes the Gaussian distribution with the expectation μ_i and variance $a_k \mu_i + b$, the camera parameters (a_k, b) represent the unique fingerprint originating from the k-th level set. Each level set is characterized by its center value u_i and allowed deviation Δ, $\mu_i \in [u_i - \frac{\Delta_i}{2}, u_i + \frac{\Delta_i}{2}]$. In practice, assuming a signal in the range $[0, 1]$, one can take fixed $\Delta_i \equiv \Delta$ and equispaced $u_i \in \{\Delta_j, j = 1, ...K = \lfloor \Delta^{-1} \rfloor\}$, where the $\lfloor . \rfloor$ indicate the rounding to the nearest larger or equal integer. It is should be noted that since the Gaussian distributed noise such as read-out noise, which is stationary and independent of the signal, does not change among different images for the same camera device, the parameter b remains the same (see details in [1]).

Then immediately, let us demonstrate our estimated camera fingerprints in comparison with the fingerprints proposed in [1]. For a fixed ISO sensitivity, the camera fingerprints (a, b) can be distinguished between *Nikon D70* and *Nikon D200*, but are not discriminative for different devices of the same camera models (see Fig. 1a). Fig. 1b illustrates that the fingerprint a_k proposed in this paper can be distinguished for different devices of the same model. Then, in the following section, based on the proposed noise model, let us establish the LRT with knowing camera and image parameters.

3. LIKELIHOOD RATIO TEST FOR TWO SIMPLE HYPOTHESIS

3.1. Problem statement

This paper aims to authenticate source devices of the same camera model based on the Poissonian-Gaussian noise model proposed in [11]. The camera device identification problem is cast in the framework of hypothesis testing theory. Then let us analyze two devices 0 and 1. Each camera device j, $j \in \{0, 1\}$ is characterized by camera parameters $(a_{k,j}, b_j)$. the problem consists in choosing between the two following hypotheses $\mathcal{H}_0$: "*the pixels z_i follow the distribution $\mathcal{N}_0$*" and $\mathcal{H}_1$: "*the pixels z_i follow the distribution $\mathcal{N}_1$*" which can be written formally as:

$$\begin{cases} \mathcal{H}_0 : \{z_i \sim \mathcal{N}_0(\mu_i, a_{k,0}\mu_i + b_0)\}, \\ \mathcal{H}_1 : \{z_i \sim \mathcal{N}_1(\mu_i, a_{k,1}\mu_i + b_1)\}. \end{cases} \qquad (2)$$

A statistical test is a mapping $\delta : \mathbb{Z}^{I \cdot J} \mapsto \{\mathcal{H}_0, \mathcal{H}_1\}$ such that hypothesis $\mathcal{H}_i$ is accepted if $\delta(\mathbf{Z}) = \mathcal{H}_i$ (see [14] for details on hypothesis testing). As previously explained, this paper focuses on the Neyman-Pearson bi-criteria approach: maximizing the correct detection probability for a given false alarm probability α_0. Let:

$$\mathcal{K}_{\alpha_0} = \left\{ \delta : \sup_{\boldsymbol{\theta}} \mathbb{P}_{\mathcal{H}_0}[\delta(\mathbf{Z}) = \mathcal{H}_1] \leq \alpha_0 \right\}, \qquad (3)$$

be the class of tests with a false alarm probability upper-bounded by α_0. Here $\mathbb{P}_{\mathcal{H}_i}[A]$ stands for the probability of event A under hypothesis $\mathcal{H}_i$, $i = \{0, 1\}$, and the supremum over $\boldsymbol{\theta}$ has to be understood
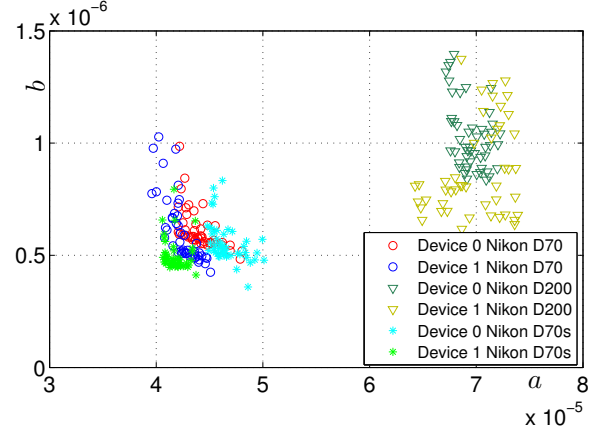
(a) Estimated camera parameters (a, b) proposed in [1] of 50 raw images.
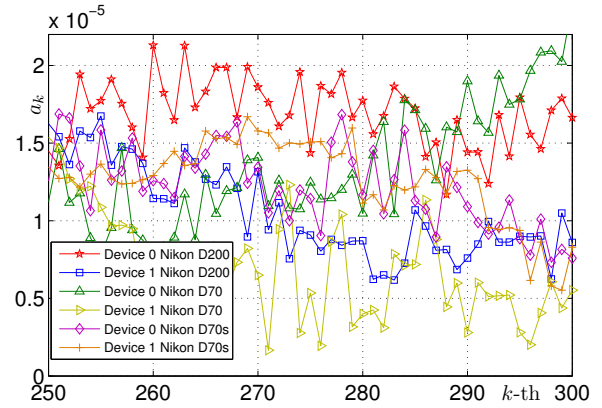
(b) Estimated camera parameter a_k in k-th level set. For simplicity, only a part of level sets are selected for comparison.

Fig. 1: Camera fingerprints comparison of different devices per camera model with ISO 200 and different camera settings. Natural raw images for *Nikon D70, Nikon D70s* and *Nikon D200* are from the Dresden image database [13].

as whatever the distribution parameters might be, in order to ensure that the false alarm probability α_0 can not be exceeded. Among all the tests in $\mathcal{K}_{\alpha_0}$, it is aimed at finding a test δ which maximizes the power function, defined by the correct detection probability:

$$\beta_\delta = \mathbb{P}_{\mathcal{H}_1}[\delta(\mathbf{Z}) = \mathcal{H}_1], \qquad (4)$$

which is equivalent to minimize the missed detection probability $\alpha_1(\delta) = \mathbb{P}_{\mathcal{H}_1}[\delta(\mathbf{Z}) = \mathcal{H}_0] = 1 - \beta_\delta$.

The main difficulty of the problem (2) is to estimate the camera parameters $(a_{k,j}, b_j)$ and image parameter μ_i. In the following subsection, we detail the statistical test that takes into account both camera and image parameters and we study the optimal detection when those parameters are known. A discussion on nuisance parameters is also provided in Section 4.

3.2. Optimal detection framework

When the camera and image parameters are known, problem (2) is reduced to a statistical test between two simple hypotheses. In such

a case, the Neyman-Pearson Lemma [14, theorem 3.2.1] states that the most powerful test in the class $\mathcal{K}_{\alpha_0}$ (3) is the LRT defined, on the assumption that pixels z_i are independent, as:

$$\delta^{\mathrm{lr}}(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 \text{ if } \Lambda^{\mathrm{lr}}(\mathbf{Z}) = \sum_{i=1}^{I} \Lambda^{\mathrm{lr}}(z_i) < \tau^{\mathrm{lr}}, \\ \mathcal{H}_1 \text{ if } \Lambda^{\mathrm{lr}}(\mathbf{Z}) = \sum_{i=1}^{I} \Lambda^{\mathrm{lr}}(z_i) \geq \tau^{\mathrm{lr}}, \end{cases} \quad (5)$$

where the decision threshold τ^{lr} is the solution of the equation $\mathbb{P}_{\mathcal{H}_0}\left[\Lambda^{\mathrm{lr}}(\mathbf{Z}) \geq \tau^{\mathrm{lr}}\right] = \alpha_0$, to ensure that the false alarm probability of the LRT equals α_0, and the log Likelihood Ratio (LR) for one observation is given by:

$$\Lambda^{\mathrm{lr}}(z_i) = \log\left(\frac{\mathcal{N}_0[z_i]}{\mathcal{N}_1[z_i]}\right). \quad (6)$$

From the definition of $\mathcal{N}_0[z_i]$ and $\mathcal{N}_1[z_i]$ (2), it is easy to write the LR (6) as:

$$\Lambda^{\mathrm{lr}}(z_i) = \log\left(\frac{\sigma_{i,0}}{\sigma_{i,1}}\right) + \frac{\sigma_{i,1}^2 - \sigma_{i,0}^2}{2\sigma_{i,1}^2\sigma_{i,0}^2}(z_i - \mu_i)^2, \quad (7)$$

where the variance $\sigma_{i,j}^2 = a_{k,j}\mu_i + b_j$, $j \in \{0,1\}$ and level set index $k \in \{1, \cdots, K\}$.

3.3. Statistical performance of LRT

Due to the fact that observations are considered to be independent, the LR $\Lambda^{\mathrm{lr}}(\mathbf{Z})$ is the sum of random variables and some asymptotic theorems allow us to establish its distribution when the number of coefficients becomes "sufficiently large". Let us denote $E_{\mathcal{H}_j}(\Lambda^{\mathrm{lr}}(z_i))$ and $V_{\mathcal{H}_j}(\Lambda^{\mathrm{lr}}(z_i))$ the expectation and the variance of the LR $\Lambda^{\mathrm{lr}}(z_i)$ under hypothesis $\mathcal{H}_j, j = \{0,1\}$. The Lindeberg's central limit theorem (CLT) [14, theorem 11.2.5] states that as I tends to infinity it holds true that[1]:

$$\frac{\sum_{i=1}^{I} \Lambda^{\mathrm{lr}}(z_i) - E_{\mathcal{H}_j}(\Lambda^{\mathrm{lr}}(z_i))}{\left(\sum_{i=1}^{I} V_{\mathcal{H}_j}(\Lambda^{\mathrm{lr}}(z_i))\right)^{1/2}} \xrightarrow{d} \mathcal{N}(0,1) , \ j = \{0,1\}, \quad (8)$$

where $\xrightarrow{d}$ represents the convergence in distribution and $\mathcal{N}(0,1)$ is the standard normal distribution, *i.e.* with zero mean and unit variance. This theorem is of crucial interest to establish the statistical properties of the proposed test [15–19]. Immediately, one can normalize under hypothesis $\mathcal{H}_0$ the LR $\Lambda^{\mathrm{lr}}(\mathbf{Z})$ as follows:

$$\overline{\Lambda}^{\mathrm{lr}}(\mathbf{Z}) = \frac{\Lambda^{\mathrm{lr}}(\mathbf{Z}) - \sum_{i=1}^{I} E_{\mathcal{H}_0}(\Lambda^{\mathrm{lr}}(z_i))}{\left(\sum_{i=1}^{I} V_{\mathcal{H}_0}(\Lambda^{\mathrm{lr}}(z_i))\right)^{1/2}}.$$

It is thus straightforward to define the normalized LRT with $\overline{\Lambda}^{\mathrm{lr}}(\mathbf{Z})$ by:

$$\overline{\delta}^{\mathrm{lr}}(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 \text{ if } \overline{\Lambda}^{\mathrm{lr}}(\mathbf{Z}) < \overline{\tau}^{\mathrm{lr}} \\ \mathcal{H}_1 \text{ if } \overline{\Lambda}^{\mathrm{lr}}(\mathbf{Z}) \geq \overline{\tau}^{\mathrm{lr}}. \end{cases} \quad (9)$$

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[1]Note that we refer to the Lindeberg's CLT, whose conditions are easily verified in our case, because the random variable are independent but are not i.i.d.

Hence, it is immediate to set the decision threshold that guarantees the prescribed false alarm probability:

$$\overline{\tau}^{\mathrm{lr}} = \Phi^{-1}\left(1 - \alpha_0\right), \quad (10)$$

where Φ and Φ^{-1} respectively represent the cumulative distribution function (cdf) of the standard normal distribution and its inverse. Similarly, denoting

$$m_j = \sum_{i=1}^{I} E_{\mathcal{H}_j}(\Lambda^{\mathrm{lr}}(z_i)); \sigma_j^2 = \sum_{i=1}^{I} V_{\mathcal{H}_j}(\Lambda^{\mathrm{lr}}(z_i)) , j=\{0,1\},$$

it is also straightforward to establish the detection function of the LRT given by:

$$\beta_{\overline{\delta}^{\mathrm{lr}}} = 1 - \Phi\left(\frac{\sigma_0}{\sigma_1}\Phi^{-1}\left(1 - \alpha_0\right) + \frac{m_0 - m_1}{\sigma_1}\right). \quad (11)$$

Equations (10) and (11) emphasize the main advantage of normalizing the LR as described in relation (9): it allows to set any of threshold that guarantees a false alarm probability independently from any distribution parameters.

4. PROPOSED DETECTOR WITH ESTIMATED CAMERA PARAMETERS

This paper employs the segmentation algorithm as our prior method [1]. The image $\mathbf{Z}$ is first transformed into the wavelet domain and then segmented into K non-overlapping homogeneous level sets, denoted S_k, of size n_k, $k \in \{1, \cdots, K\}$. Among each level set S_k, all the pixels are assumed to follow the Gaussian distribution independently and identically. Then, let us denote $\mathbf{z}_k^{\mathrm{wapp}} = \{z_{k,i}^{\mathrm{wapp}}\}_{i=1}^{n_k}$ and $\mathbf{z}_k^{\mathrm{wdet}} = \{z_{k,i}^{\mathrm{wdet}}\}_{i=1}^{n_k}$ as the vector of wavelet approximation coefficients and detail coefficients respectively. Since the wavelet transformation is linear, the proposed noise model in the spatial domain can be used in the wavelet domain (see details in [11]). Immediately, the coefficients $z_{k,i}^{\mathrm{wapp}}$ and $z_{k,i}^{\mathrm{wdet}}$ follows the Gaussian distribution:

$$z_{k,i}^{\mathrm{wapp}} \sim \mathcal{N}(\mu_k, \|\phi\|_2^2\sigma_k^2) \quad (12)$$
$$z_{k,i}^{\mathrm{wdet}} \sim \mathcal{N}(0, \sigma_k^2) \quad (13)$$

where $\sigma_k^2 = a_k\mu_k + b$ denoting the linear relationship between the expectation and variance. ϕ denotes the 2D normalized wavelet scaling function. Then in k-th level set, the ML (Maximum Likelihood) estimated local mean $\widehat{\mu}_k = \frac{1}{n_k}\sum_{i=1}^{n_k} z_{k,i}^{\mathrm{wapp}}$ and local variance $\widehat{v}_k = \frac{1}{n_k-1}\sum_{i=1}^{n_k}(z_{k,i}^{\mathrm{wdet}} - \frac{1}{n_k}\sum_{i=1}^{n_k} z_{k,i}^{\mathrm{wdet}})^2$ are averaged by:

$$\widehat{\mu}_k^{\star} = \frac{1}{N \cdot n_k}\sum_{n=1}^{N}\sum_{i=1}^{n_k} z_{k,i}^{\mathrm{wapp}} \quad (14)$$

$$\widehat{v}_k^{\star} = \frac{1}{N \cdot (n_k - 1)}\sum_{n=1}^{N}\sum_{i=1}^{n_k}(z_{k,i}^{\mathrm{wdet}} - \frac{1}{n_k}\sum_{i=1}^{n_k} z_{k,i}^{\mathrm{wdet}})^2 \quad (15)$$

where the vector $n \in \{1, \cdots, N\}$ denoted as the number of multiple images. Then the camera parameters $(\widehat{a}_k, \widehat{b})$ can be given by:

$$\widehat{a}_k = \frac{\widehat{v}_k^{\star} - \widehat{b}}{\widehat{\mu}_k^{\star}} \quad (16)$$

where $\widehat{b}$ is estimated by using the algorithm proposed by [1].

In Section 3 the framework of hypothesis testing theory has been presented assuming that all the model parameters are known for each pixel. On the assumption that the camera parameters $(a_{k,0}, b_0)$ and $(a_{k,1}, b_1)$ are known and image parameter μ_k are unknown, the proposed practical test detects the given image $\mathbf{Z}$ which is either acquired by camera device 0 or camera device 1. A usual solution consists in replacing the unknown parameter by its ML estimation. This leads to the construction of the following practical test:

$$\widehat{\delta}(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 \text{ if } \widehat{\Lambda}(\mathbf{Z}) = \sum_{k=1}^{K}\sum_{i=1}^{n_k} \widehat{\Lambda}(z_{k,i}^{\text{wapp}}) < \widehat{\tau}, \\ \mathcal{H}_1 \text{ if } \widehat{\Lambda}(\mathbf{Z}) = \sum_{k=1}^{K}\sum_{i=1}^{n_k} \widehat{\Lambda}(z_{k,i}^{\text{wapp}}) \geq \widehat{\tau}, \end{cases} \quad (17)$$

where $\widehat{\tau}$ the solution of equation $\mathbb{P}_{\mathcal{H}_0}[\widehat{\Lambda}(\mathbf{Z}) \geq \widehat{\tau}] = \alpha_0$ and the decision statistic $\widehat{\Lambda}(z_{k,i}^{\text{wapp}})$ for each pixel is given by:

$$\widehat{\Lambda}(z_{k,i}^{\text{wapp}}) = \frac{1}{2} \log \frac{a_{k,0}\widehat{\mu}_k + b_0}{a_{k,1}\widehat{\mu}_k + b_1}$$
$$+ \frac{1}{2}\Big(\frac{1}{a_{k,0}\widehat{\mu}_k + b_0} - \frac{1}{a_{k,1}\widehat{\mu}_k + b_1}\Big) \cdot \frac{(z_{k,i}^{\text{wapp}} - \widehat{\mu}_k)^2}{\|\phi\|_2^2}.$$
$$(18)$$

In order to have a normalized decision statistic for the whole image, $\widehat{\Lambda}(\mathbf{Z})$ is redefined as:

$$\widehat{\Lambda}(\mathbf{Z}) = \frac{1}{S_L}\sum_{k=1}^{K}\sum_{i=1}^{n_k}\widehat{\Lambda}(z_{k,i}^{\text{wapp}}) - E_{\mathcal{H}_0}(\widehat{\Lambda}) \quad (19)$$
with
$$S_L^2 = \sum_{k=1}^{K}\sum_{i=1}^{n_k} V_{\mathcal{H}_0}(\widehat{\Lambda}).$$

5. NUMERICAL EXPERIMENTS

To verify the sharpness of the theoretically established results, it is proposed to use a Monte Carlo simulation on a synthetic image with 1000 repetitions on the assumption of different pixel number. Fig. 2a illustrates the detection performance as a Receiver Operating Character (ROC) respectively for $I = \{50, 100, 200, 500\}$ pixels where the camera device 0 and 1 are characterized by $(a_{k,0}, b_0)$ and $(a_{k,1}, b_1)$. Before testing, the fingerprints are estimated previously by using our proposed algorithms (see details in Section 4). As Fig. 2a showed, the test performs better and better with increasing the number of pixels. It is should be noted that due to limited writing space, camera fingerprints can not be illustrated in this paper.

		min. P_E	Power $\alpha_0 = 0.05$
Proposed test	Nikon D70	0.065	0.91
	Nikon D70s	0.070	0.89
	Nikon D200	0.015	0.98
Test [10]	Nikon D70	0.005	1.0
	Nikon D70s	0.01	1.0
	Nikon D200	0.015	1.0
Test [1]	Nikon D70	0.375	0.23
	Nikon D70s	0.305	0.33
	Nikon D200	0.415	0.05

Table 1: Empirical performance between the proposed test, the one proposed in [1] also based on heteroscedastic noise and the well-known PRNU PCE from [10].
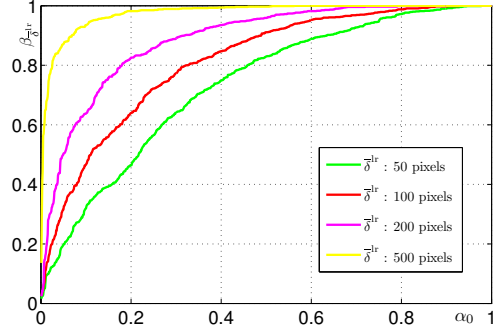
(a) The detection performance of the test $\overline{\delta}^{\text{lr}}$ on the assumption of knowing camera and image parameter.
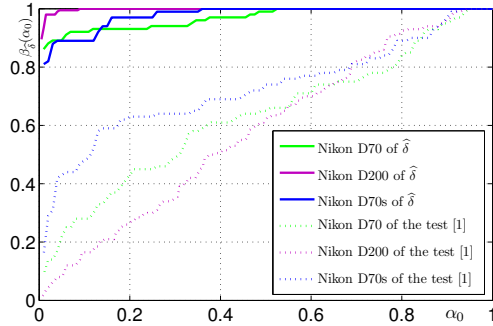
(b) The detection performance of the test $\widehat{\delta}$: parameter $(a_{k,0}, b_0)$ and $(a_{k,1}, b_1)$ are known, μ_k are unknown.

Fig. 2: Illustration of ROC curves comparison on simulated and real images. All the camera settings for ISO equal 200.

Finally, let us demonstrate the detection performance on the real images. In our experiments, the Dresden image database is used [13]. All full-resolution images are selected from three camera models *Nikon D70, Nikon D70s* and *Nikon D200* where each camera model has two devices. First, it is proposed to divide each set of images from each device into two subsets: "*Learning Subset*" and "*Testing Subset*". Images of "*Learning Subset*" are used to extract device fingerprints; images of "*Testing Subset*" are used to identify the origin of a given image. It should be noted that "*Learning Subset*" and "*Testing Subset*" do not have any intersection. The number of "*Learning Subset*" is set as 100. As Fig. 2b illustrated , our proposed detector has the considerable ability of identifying the camera devices with a high performance. Nevertheless, the detector of [1] nearly can not identify the different devices of the same model. Moreover, let us illustrate the emperical performance at the give FAR α_0 and its minimal Prediction Error (P_E) in Table 1. The performance of our proposed test is very close to the prior-art detector [10] and better than the test [1].

6. CONCLUSION

This paper studies the problem of identifying the source camera device. Based on the Poissonian-Gaussian noise model, the problem is cast in the framework of hypothesis testing theory. Assuming that the camera and image parameters are prior known, the statistical performance of the LRT is analytically established. In the practical case, based on the estimated image parameters, our designed test outperforms the detector of [1].

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