Optimal Detector for Camera Model Identification Based on DCT Coefficient Statistics

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***Abstract*—The goal of this paper is to design a statistical test for the camera model identification problem. The approach is based on the state-of-the-art model of Discret Cosine Transform (DCT) coefficients to capture their statistical difference, which jointly results from different sensor noises and in-camera processing algorithms. The noise model parameters are considered as camera fingerprint to identify camera models. The camera model identification problem is cast in the framework of hypothesis testing theory. In an ideal context where all model parameters are perfectly known, this paper studies the optimal detector given by the Likelihood Ratio Test (LRT) and analytically establishes its statistical performances. In practice, a Generalized LRT is designed to deal with the difficulty of unknown parameters such that it can meet a prescribed false alarm probability while ensuring a high detection performance. Numerical results on simulated database and natural JPEG images highlight the relevance of the proposed approach.**

***Index Terms*—Hypothesis Testing, Digital Forensics, Camera Model Identification, Natural Image Model, Nuisance Parameters.**

I. Introduction

The evolution of digital imaging technology and information technologies in the past decades has raised a number of information security challenges [1]. Digital image forensics has been emerged to restore the trust to digital images. One of the key problems of digital image forensics is image origin identification, which aims to verify whether a given image was taken from a specific camera or a certain camera model. Active forensics addresses this problem by generating extrinsically security measures such as digital signatures and digital watermarks, referred to as extrinsic fingerprint, and adding them to the image file. However, this approach is of limited extent due to many strict constraints in its protocols. Passive forensics has been quickly evolved in order to solve the problem of image origin identification in its entirety. Passive forensics works on an assumption that when an image is captured by a camera, the image contains some internal traces left from the camera, which are called intrinsic fingerprints.

Every stage from real-world scene acquisition to image storage can provide clues for forensic analysis. Several fingerprints have been proposed in the literature for image origin identification such as lens aberration [2], Sensor Pattern Noise (SPN) [3], Color Filter Array (CFA) pattern and interpolation [4], white-balancing [5], and JPEG compression [6]. Even though those methods perform efficiently, they have been designed with a very limited exploitation of hypothesis testing theory and statistical image models. Therefore, their performance can not be analytically established and is only evaluated based on a large image database. Moreover, in the operational context, it is crucial to warrant a prescribed false alarm probability.

This paper proposes a statistical test within hypothesis testing framework for camera model identification, which is based on the same methodology proposed in our previous works [7], [8]. The approach is based on the state-of-the-art model of Discret Cosine Transform (DCT) coefficients to capture their statistical difference that jointly results from different sensor noises and in-camera processing algorithms. The contribution of this paper is threefold. Firstly, the paper proposes a novel fingerprint that is further exploited for camera model identification. Secondly, based on the parametric model of DCT coefficients, the paper casts the problem of camera model identification into hypothesis testing framework and studies the optimal detector given by the Likelihood Ratio Test (LRT) in an ideal context where all model parameters are known. For a practical use, the Generalized Likelihood Ratio Test (GLRT) is designed to deal with the difficulty of unknown parameters. The statistical performance of the proposed tests can be analytically established. The proposed GLRT can guarantee a prescribed false alarm probability.

The paper is organized as follows. Section II presents the camera fingerprint that is further exploited for camera model identification. Section III states the camera model identification problem in the framework of hypothesis testing theory and studies the most powerful LRT. Section IV designs the GLRT to overcome the difficulty of unknown image parameters. Section V presents numerical results of the proposed tests on simulated and real natural JPEG images. Finally, Section VI concludes the paper.

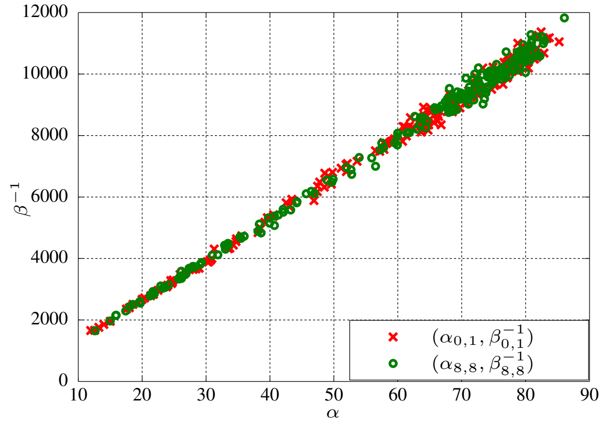

Fig. 1. Estimated parameters (α, β) at frequency $(0, 1)$ and $(8, 8)$ of uniform images generated using $\tilde{a} = 0.1$, $\tilde{b} = 2$, $\gamma = 2.2$.

II. Camera Fingerprint

To design a camera fingerprint, it is necessary to study image characteristics during various stages of image processing pipeline. Typically, the image processing pipeline is composed of three main stages: RAW image acquisition, post-acquisition processing such as demosaicing, white-balancing, gamma correction, and JPEG compression.

The study of noise statistics in the spatial domain has been performed in our previous work [9]. Firstly, the approach starts from the heteroscedastic noise model proposed in [7] given as

$$x_i \sim \mathcal{N}\big(\mu_{x_i}, a\mu_{x_i} + b\big), \tag{1}$$

where x_i denotes a RAW pixel. The index of color channel is omitted for simplicity. By convention, μ_X and σ_X^2 denote respectively expectation and variance of a random variable X. The parameters (a, b) was proposed in our previous work [7] as fingerprint for camera model identification from RAW images. Then, that approach [9] takes into account the non-linear effect of gamma correction to develop a generalized noise model

$$\sigma_{z_i}^2 = \frac{1}{\gamma^2}\mu_{z_i}^{2-2\gamma}(\tilde{a}\mu_{z_i}^{\gamma} + \tilde{b}), \tag{2}$$

where z_i denotes a TIFF pixel, γ is the correction factor, and $(\tilde{a}, \tilde{b})$ differ from the parameters (a, b) due to the operations of demosaicing and white balancing. Similarly, the parameters $(\tilde{a}, \tilde{b}, \gamma)$ are proposed in [8] as fingerprint to identify camera models from JPEG images.

The next step in image processing pipeline is JPEG compression that involves transforming the TIFF image into the DCT domain. To capture statistics of DCT coefficients accurately, it is necessary to study the model of DCT coefficients. Based on the assumption that the pixels are identically distributed within 8×8 block, our previous work [10]–[12] has recently proposed a novel model of DCT coefficients, given by

$$f_I(u) = \sqrt{\frac{2}{\pi}}\frac{\Big(|u|\sqrt{\frac{\beta}{2}}\Big)^{\alpha-\frac{1}{2}}}{\beta^{\alpha}\Gamma(\alpha)}K_{\alpha-\frac{1}{2}}\Big(|u|\sqrt{\frac{2}{\beta}}\Big), \tag{3}$$

where f_X denotes the probability density function (pdf) with respect to a random variable X, α is a positive shape parameter, β is a positive scale parameter, $\Gamma(\cdot)$ denotes the gamma function and $K_{\nu}(x)$ denotes the modified Bessel function [13, chap. 5.5]. The proposed model of DCT coefficients outperforms the Laplacian, Generalized Gaussian, and Generalized Gamma model. The parameters (α, β) can be estimated following the Maximum Likelihood (ML) approach as proposed in [12].

Since the parameters $(\tilde{a}, \tilde{b}, \gamma)$ also contain information about camera model, after transforming into DCT domain, this information is expanded over different frequencies. Therefore, it is proposed to establish the relation between the parameters $(\tilde{a}, \tilde{b}, \gamma)$ and (α, β) to capture such information in the DCT domain. For the sake of simplicity, this relation is given by

$$\beta^{-1} = c\,\alpha + d, \tag{4}$$

where the parameters (c, d) depend on $(\tilde{a}, \tilde{b}, \gamma)$. Due to limited space, the proof will be omitted in this paper. The relation (4) suggests that the parameters (c, d) can be also used for camera model identification. It can be said that while the relations (1) and (2) characterize the non-stationarity of noise in the spatial domain, the relation (4) characterizes this property in the DCT domain. The parameters (c, d) are proposed to be exploited as camera fingerprint to identify camera models in this paper.

III. Optimal Detector for Camera Model Identification Problem

It should be noted that in an image whose each 8×8 block is uniform, the same parameters (α, β) and (c, d) are shared among DCT coefficients at different frequencies. The relation (4) on such images is illustrated in Fig. 1. However, because of heterogeneity in a natural image, the energy tends to be more located in lower frequencies. Consequently, DCT coefficients at different frequencies do not share the same parameters (α, β) and (c, d). It is proposed to arrange DCT coefficients into 64 vectors of coefficients according to the zig-zag order. Let $\boldsymbol{I}_k = (I_{k,1}, \ldots, I_{k,N_b})$ with $k \in \{1, \ldots, 64\}$, be the vector of length N_b that contains coefficients at the frequency k. Analogously, let denote the parameters (α_k, β_k) and (c_k, d_k) with respect to the AC coefficients $\boldsymbol{I}_k$.

A. Hypothesis Testing Formulation

In order to attenuate the impact of image content, a pre-processing stage involves performing a denoising filter on the inspected image $\mathbf{Z}$ then transforming the residual image into the DCT domain.

Let analyze two camera models $\mathcal{S}_0$ and $\mathcal{S}_1$. Each camera model $\mathcal{S}_j$, $j \in \{0, 1\}$, is characterized by the parameters $(c_{k,j}, d_{k,j})$ where K is the number of usable frequencies for camera model identification. For obvious reasons, it is assumed that $(c_{k,0}, d_{k,0}) \neq (c_{k,1}, d_{k,1})$. In a binary hypothesis testing, the inspected image $\mathbf{Z}$ is either acquired by camera model $\mathcal{S}_0$ or camera model $\mathcal{S}_1$. The goal of the test is to decide between two hypotheses defined by $\forall k \in \{1,\dots,K\}, \forall i \in \{1,\dots,N_b\}$

$$\begin{cases} \mathcal{H}_0 = \Big\{ I_{k,i} \sim P_{\boldsymbol{\theta}_{k,0}}, \beta_{k,0}^{-1} = c_{k,0}\alpha_k + d_{k,0} \Big\} \\ \mathcal{H}_1 = \Big\{ I_{k,i} \sim P_{\boldsymbol{\theta}_{k,1}}, \beta_{k,1}^{-1} = c_{k,1}\alpha_k + d_{k,1} \Big\}, \end{cases} \tag{5}$$

where $P_{\boldsymbol{\theta}_{k,j}}$, $\boldsymbol{\theta}_{k,j} = (\alpha_k, c_{k,j}, d_{k,j})$, denotes the statistical distribution of DCT coefficients $I_{k,i}$ under hypothesis $\mathcal{H}_j$. Let

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

be the class of tests whose the false alarm probability is upper-bounded by the prescribed rate α_0. Here $\boldsymbol{\theta}_0 = (\boldsymbol{\theta}_{1,0}, \dots, \boldsymbol{\theta}_{K,0})$ is the vector containing all parameters, $\mathbb{P}_{\mathcal{H}_j}\big[E\big]$ stands for the probability of event E under hypothesis $\mathcal{H}_j$, $j \in \{0, 1\}$, and the supremum over $\boldsymbol{\theta}$ has to be understood as whatever model parameters might be. Among all the tests in the class $\mathcal{K}_{\alpha_0}$, it is aimed at finding a test δ which maximizes the power function, defined by the correct detection probability:

$$\beta_\delta = \mathbb{P}_{\mathcal{H}_1}\Big[\delta(\mathbf{Z}) = \mathcal{H}_1\Big].$$

The problem (5) highlights the difficulties of the camera model identification since the parameters $(\alpha_k, c_{k,j}, d_{k,j})$ are unknown in practice. The main goal of this paper is to study the LRT when all model parameters are known and to design the GLRT to deal with the difficulty of unknown parameters α_k. The parameters $(c_{k,j}, d_{k,j})$ are assumed to be known in advance.

B. Likelihood Ratio Test for Two Simple Hypotheses

When all model parameters are known, in virtue of the Neyman-Pearson lemma [14, theorem 3.2.1], the most powerful test δ^* solving the problem (5) is the LRT given by the following decision rule

$$\delta^*(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 & \text{if} \quad \Lambda(\mathbf{Z}) = \sum_{k=1}^K \sum_{i=1}^{N_b} \Lambda(I_{k,i}) < \tau^* \\ \mathcal{H}_1 & \text{if} \quad \Lambda(\mathbf{Z}) = \sum_{k=1}^K \sum_{i=1}^{N_b} \Lambda(I_{k,i}) \geq \tau^* \end{cases} \tag{6}$$

where the LR $\Lambda(I_{k,i})$ is defined as

$$\Lambda(I_{k,i}) = \log \frac{P_{\boldsymbol{\theta}_{k,1}}\big[I_{k,i}\big]}{P_{\boldsymbol{\theta}_{k,0}}\big[I_{k,i}\big]}. \tag{7}$$

From (3), it can be noted that the expression of the LR $\Lambda(I_{k,i})$ is difficult to exploit for subsequent stages, e.g. the design of the GLRT and analytic establishment of its statistical performance. Therefore it is proposed to simplify the LR $\Lambda(I_{k,i})$ to facilitate the study in the manner that it does not cause any loss of optimality.

Using the Laplace's approximation [15], the function $f_I(u)$ can be approximated as

$$f_I(u) \approx \frac{|u|^{\alpha-1}}{(2\beta)^{\frac{\alpha}{2}}\Gamma(\alpha)} \exp\left(-|u|\sqrt{\frac{2}{\beta}}\right). \tag{8}$$

Consequently, the LR $\Lambda(I_{k,i})$ can be simplified as

$$\Lambda(I_{k,i}) = \frac{\alpha_k}{2}\log\frac{\beta_{k,1}^{-1}}{\beta_{k,0}^{-1}} - \sqrt{2}|I_{k,i}|\Big(\sqrt{\beta_{k,1}^{-1}} - \sqrt{\beta_{k,0}^{-1}}\Big). \tag{9}$$

The main advantage of the Laplace's approximation (8) is to provide an approximation of the form of exponential family function, which allows us to simplify the expression of the LR $\Lambda(I_{k,i})$. The approximating function (8) is used only for simplification of the LR. The estimation of parameters (α_k, β_k) is always based on the exact function (3).

In order to analytically establish the statistical performance of the LRT, it is necessary to characterize the statistical distribution of the LR $\Lambda(\mathbf{Z})$ under each hypothesis $\mathcal{H}_j$. To this end, it is proposed to rely on the Lindeberg Central Limit Theorem (CLT) [14, theorem 11.2.5] that requires to calculate the expectation and variance of $\Lambda(I_{k,i})$.

Proposition 1. *Under hypothesis $\mathcal{H}_j$, the first two moments of the LR $\Lambda(I_{k,i})$ are given by*

$$m_{k,j} \triangleq \mathbb{E}_{\mathcal{H}_j}\Big[\Lambda(I_{k,i})\Big] = \frac{\alpha_k}{2}\log\frac{\beta_{k,1}^{-1}}{\beta_{k,0}^{-1}} - \frac{2}{\sqrt{\pi}}\beta_{k,j}^{\frac{1}{2}}\frac{\Gamma(\alpha_k+\frac{1}{2})}{\Gamma(\alpha_k)}\Big(\sqrt{\beta_{k,1}^{-1}} - \sqrt{\beta_{k,0}^{-1}}\Big) \tag{10}$$

$$v_{k,j} \triangleq \mathrm{Var}_{\mathcal{H}_j}\Big[\Lambda(I_{k,i})\Big] = 2\Big(\sqrt{\beta_{k,1}^{-1}} - \sqrt{\beta_{k,0}^{-1}}\Big)^2 \times \Big(\alpha_k\beta_{k,j} - \frac{2\beta_{k,j}}{\pi}\frac{\Gamma^2(\alpha_k+\frac{1}{2})}{\Gamma^2(\alpha_k)}\Big). \tag{11}$$

where $\mathbb{E}_{\mathcal{H}_j}[\cdot]$ and $\mathrm{Var}_{\mathcal{H}_j}[\cdot]$ respectively denote the mathematical expectation and variance under hypothesis $\mathcal{H}_j$.

Proof: Due to limited space, the proof is only briefly presented. It can be noted from (9) that it is necessary to calculate the expectation and variance of the random variable $|I|$. According to [12], the coefficient I is normally distributed with zero-mean and variance σ_b^2 which is itself a random variable following the Gamma distribution $\mathcal{G}(\alpha, \beta)$. Therefore, given a constant variance σ_b^2, the random variable $|I|$ follows the half-Normal distribution. Based on the law of total expectation, the mathematical expectation and variance of $|I|$ are given by

$$\mathbb{E}\Big[|I|\Big] = \sqrt{\frac{2}{\pi}}\beta^{\frac{1}{2}}\frac{\Gamma(\alpha+\frac{1}{2})}{\Gamma(\alpha)} \tag{12}$$

$$\mathrm{Var}\Big[|I|\Big] = \alpha\beta - \frac{2\beta}{\pi}\frac{\Gamma^2(\alpha+\frac{1}{2})}{\Gamma^2(\alpha)}. \tag{13}$$

The proof follows immediately. ■

In virtue of Lindeberg CLT, the statistical distribution of the LR $\Lambda(\mathbf{Z})$ under hypothesis $\mathcal{H}_j$ is derived as

$$\Lambda(\mathbf{Z}) \xrightarrow{d} \mathcal{N}\big(m_j, v_j\big), \tag{14}$$

where the notation $\xrightarrow{d}$ denotes the convergence in distribution and the expectation m_j and variance v_j are given by

$$m_j = \sum_{k=1}^K \sum_{i=1}^{N_b} \mathbb{E}_{\mathcal{H}_j}\Big[\Lambda(I_{k,i})\Big] = \sum_{k=1}^K N_b m_{k,j} \tag{15}$$

$$v_j = \sum_{k=1}^K \sum_{i=1}^{N_b} \mathrm{Var}_{\mathcal{H}_j}\Big[\Lambda(I_{k,i})\Big] = \sum_{k=1}^K N_b v_{k,j}. \tag{16}$$

Since a natural image is heterogeneous, it is proposed to normalize the LR $\Lambda(\mathbf{Z})$ in order to set the decision threshold independently of the image content. The normalized LR is defined by $\Lambda^\star(\mathbf{Z}) = \frac{\Lambda(\mathbf{Z})-m_0}{\sqrt{v_0}}$. Accordingly, the corresponding LRT $\delta^\star$ is rewritten as follows

$$\delta^\star(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 & \text{if} \quad \Lambda^\star(\mathbf{Z}) < \tau^\star \\ \mathcal{H}_1 & \text{if} \quad \Lambda^\star(\mathbf{Z}) \geq \tau^\star \end{cases} \tag{17}$$

where the decision threshold $\tau^\star$ is the solution of the equation $\mathbb{P}_{\mathcal{H}_0}\left[\Lambda^\star(\mathbf{Z}) \geq \tau^\star\right] = \alpha_0$. The decision threshold $\tau^\star$ and the power $\beta_{\delta^\star}$ are given in following theorem.

Theorem 1. *In an ideal context where all the model parameters $(\alpha_k, c_{k,j}, d_{k,j})$ are exactly known, the decision threshold and the power function of the LRT $\delta^\star$ are given by*

$$\tau^\star = \Phi^{-1}(1-\alpha_0) \tag{18}$$

$$\beta_{\delta^\star} = 1 - \Phi\left(\frac{m_0 - m_1 + \tau^\star\sqrt{v_0}}{\sqrt{v_1}}\right), \tag{19}$$

where $\Phi(\cdot)$ and $\Phi^{-1}(\cdot)$ denotes respectively the cumulative distribution function of the standard Gaussian random variable and its inverse.

The test power $\beta_{\delta^\star}$ serves as an upper-bound of any statistical test for the camera model identification problem.

IV. Practical Context: Generalized Likelihood Ratio Test

In this section it is assumed that the camera parameters $(c_{k,j}, d_{k,j})$ are known and we only deal with unknown nuisance parameters α_k. By replacing unknown parameter α_k by its ML estimate $\hat{\alpha}_k$ in the LR $\Lambda(I_{k,i})$ (9) (see more details about ML estimation of parameters (α_k, β_k) in [12]), the Generalized Likelihood Ratio (GLR) $\widehat{\Lambda}(I_{k,i})$ can be given by

$$\widehat{\Lambda}(I_{k,i}) = \frac{\hat{\alpha}_k}{2}\log\frac{c_{k,1}\hat{\alpha}_k + d_{k,1}}{c_{k,0}\hat{\alpha}_k + d_{k,0}} - \sqrt{2}|I_{k,i}|\Big(\sqrt{c_{k,1}\hat{\alpha}_k + d_{k,1}} - \sqrt{c_{k,0}\hat{\alpha}_k + d_{k,0}}\Big). \tag{20}$$

The ML estimate $\hat{\alpha}_k$ is asymptotically consistent [14], i.e. it asymptotically converges in probability to its true value: $\hat{\alpha}_k \xrightarrow{P} \alpha_k$. Therefore, from the Slutsky's theorem [14, theorem 11.2.11], the statistical distribution of the GLR $\widehat{\Lambda}(\mathbf{Z}) = \sum_{k=1}^{K}\sum_{i=1}^{N_b}\widehat{\Lambda}(I_{k,i})$ under each hypothesis $\mathcal{H}_j$ can be approximated as

$$\widehat{\Lambda}(\mathbf{Z}) \xrightarrow{d} \mathcal{N}\big(m_j, v_j\big), \tag{21}$$

where the expectation m_j and variance v_j are given in (15) and (16), respectively.

Similarly, it is proposed to normalize the GLR $\widehat{\Lambda}(\mathbf{Z})$ to set the decision threshold independently of image content. The normalized GLR $\widehat{\Lambda}^\star(\mathbf{Z})$ is defined by $\widehat{\Lambda}^\star(\mathbf{Z}) = \frac{\widehat{\Lambda}(\mathbf{Z})-m_0}{\sqrt{v_0}}$. However, the expectation m_0 and variance v_0 can not be defined in practice since the parameters α_k are unknown. Therefore, this paper proposes to replace α_k by $\hat{\alpha}_k$ in (15) and (16) to obtain the estimates of m_0 and v_0, denoted $\hat{m}_0$ and $\hat{v}_0$. The normalized GLR $\widehat{\Lambda}^\star(\mathbf{Z})$ can be given in practice as $\widehat{\Lambda}^\star(\mathbf{Z}) = \frac{\widehat{\Lambda}(\mathbf{Z})-\hat{m}_0}{\sqrt{\hat{v}_0}}$. Finally, the GLRT $\widehat{\delta}^\star$ based on the normalized GLR $\widehat{\Lambda}^\star(\mathbf{Z})$ is given by

$$\widehat{\delta}^\star(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 & \text{if} \quad \widehat{\Lambda}^\star(\mathbf{Z}) < \widehat{\tau}^\star \\ \mathcal{H}_1 & \text{if} \quad \widehat{\Lambda}^\star(\mathbf{Z}) \geq \widehat{\tau}^\star \end{cases} \tag{22}$$

where the decision threshold $\widehat{\tau}^\star$ is the solution of the equation $\mathbb{P}_{\mathcal{H}_0}\left[\widehat{\Lambda}^\star(\mathbf{Z}) \geq \widehat{\tau}^\star\right] = \alpha_0$. Still from the Slutsky's theorem, the decision threshold and the power of the GLRT $\widehat{\delta}^\star$ can be accordingly defined as in the Theorem 1.

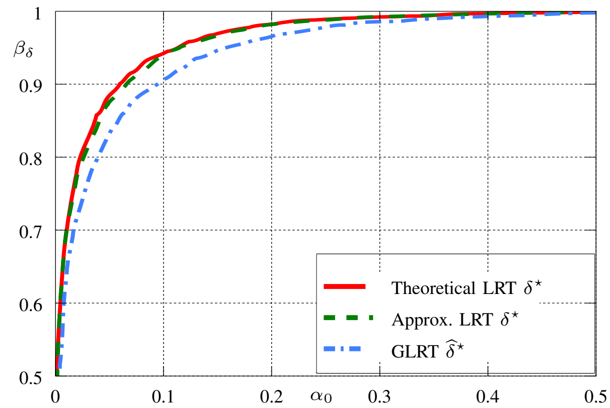

Fig. 2. Detection performance of proposed tests on simulated vectors with 1024 coefficients.

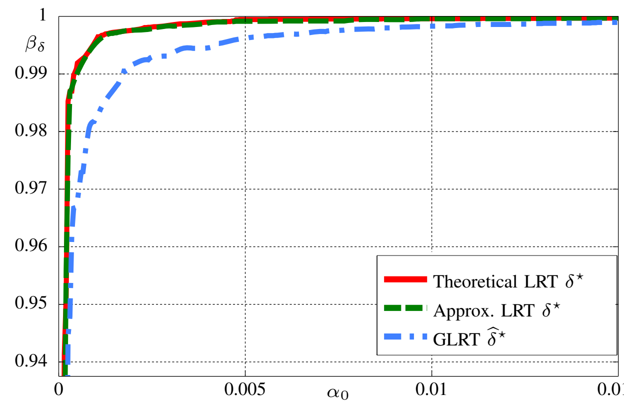

Fig. 3. Detection performance of proposed tests on simulated vectors with 1024 coefficients.

V. Numerical Results

A. Detection Performance on Simulated Database

The detection performance of proposed tests is first theoretically studied on simulated database. Suppose that the camera models $\mathcal{S}_0$ and $\mathcal{S}_1$ are characterized by the parameters $(c_0, d_0) = (11.8, -3.5)$ and $(c_1, d_1) = (13.5, -4.5)$, respectively. These parameters correspond to frequency $(8, 8)$ of JPEG images taken by *Canon Ixus 70* and *Nikon D200* camera models in the Dresden image database [16], respectively. They are used to generate randomly 5000 vectors of 1024 and 4096 coefficients under $\mathcal{H}_0$ and $\mathcal{H}_1$. Because this paper proposes to

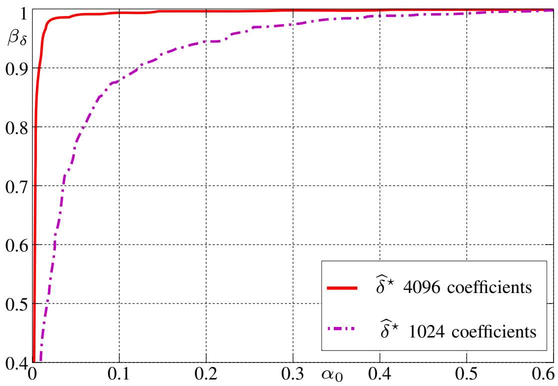

Fig. 4. Detection performance of the proposed GLRT $\widehat{\delta}^\star$ for different number of coefficients extracted randomly at frequency $(8, 8)$ of natural JPEG images taken by *Canon Ixus 70* and *Nikon D200* camera models.

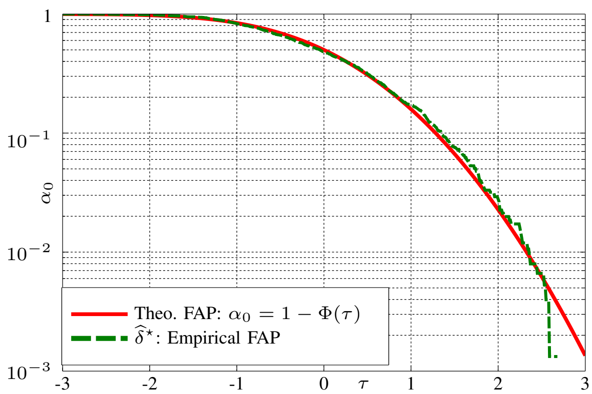

Fig. 5. Comparison between the theoretical false alarm probability (FAP) and the empirical FAP, plotted as a function of decision threshold τ.

simplify the LR $\Lambda(I_{k,i})$ to facilitate the study, it is desirable to compare the detection performance of the LRT based on the approximating LR with the one based on the exact LR. The expectation and variance of the exact LR are calculated numerically. Moreover, it is necessary to compare the detection performance of the proposed GLRT with the LRT since the former utilizes ML estimate of unknown parameter α_k, which may cause a loss of power. Fig. 2 and Fig. 3 show the detection performance of all proposed tests for 1024 and 4096 coefficients, respectively. For clarity, only regions of interest are illustrated in the figures. It is worth noting that the loss of power between the theoretical LRT and approximating LRT is negligible. Besides, a small loss of power is revealed between the GLRT and LRT due to the estimation of unknown parameters. Nevertheless this loss of power decreases when the number of coefficients increases. The power function of all proposed tests is perfect (e.g. $\beta_\delta = 1$) from 2^{14} coefficients for any false alarm rate α_0.

B. Detection Performance on Two Canon Ixus 70 *and* Nikon D200 *Camera Models*

To highlight the relevance of the proposed GLRT, two *Canon Ixus 70* and *Nikon D200* camera models of the Dresden image database [16] are chosen to conduct experiments. The *Canon Ixus 70* and *Nikon D200* cameras are respectively set at $\mathcal{H}_0$ and $\mathcal{H}_1$. All available JPEG images of each camera model are used in this experiment. The reference camera parameters are estimated as discussed above. The Fig. 4 shows the detection performance of the GLRT $\widehat{\delta}^\star$ for 1024 and 4096 coefficients extracted randomly at frequency $(8, 8)$ of natural images taken by *Canon Ixus 70* and *Nikon D200* camera models. We can note a similar behavior to the detection performance on simulated database.

Meanwhile, the Fig. 5 shows the comparison between the theoretical and empirical false alarm probability, which are plotted as a function of decision threshold τ. The proposed GLRT $\widehat{\delta}^\star$ shows an ability of guaranteeing a prescribed false alarm rate, even though there is a slight difference in some cases (typically $\alpha_0 \leq 10^{-3}$) due to the influence of image content and the inaccuracy of the CLT for modeling tails.

VI. Conclusion

This paper proposes a novel approach for camera model identification, that is based on the state-of-the-art model of DCT coefficients to a statistical test within hypothesis testing framework. The parameters (c, d) characterizing the simplistic linear relation between α and β^{-1}, which are two parameters of the DCT coefficient model, are proposed to be exploited as camera fingerprint for camera model identification. The optimal detector given by the LRT is studied in the theoretical context and the adaptive GLRT is designed to deal with the difficulty of unknown parameters in practice. The strength of the proposed approach is that statistical performance of the tests can be analytically established as well as they can warrant a prescribed false alarm rate while ensuring a high detection performance.

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