FORENSIC SENSOR PATTERN NOISE EXTRACTION FROM LARGE IMAGE DATA SET

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ABSTRACT

The sensor pattern noise (SPN) can be regarded as the unique identity of a digital camera which is highly useful in digital image forensics [1, 2]. Existing methods [1, 2] which works by denoising each individual natural image often took an investigator a long time and great efforts to collect sufficient photos of diversified enough natural scenes. These processes are hard to repeat or standardized for officially using by an authority. In this work, we create noise image data set by taking photos of random noises displayed on a high definition monitor and propose a homomorphic based SPN extraction method. It offers the forensic researcher a fast way to create a large image data set in a few minutes. And the extraction method only needs to denoise once, which is highly efficient to deal with large numbers of photos. We compared the source camera identification performance of the proposed SPN extraction method to a prior state-of-art with identical experimental settings. The experimental results confirm the effectiveness of the proposed method.

***Index Terms*—** Digital Forensics, Sensor Pattern Noise, Source Camera Identification, PRNU.

1. INTRODUCTION

The sensor pattern noise (SPN) can be regarded as the unique identity of a digital camera which is highly useful in digital image forensics[1, 2]. It is caused by tiny flaws in the process of semiconductor manufacturing of CCD/CMOS sensor chips of digital cameras. Flaw position occurs randomly in each sensor chip, and the introduced noise level is also certain[3]. Thus, there is certain correlation between SPN of two images photographed by the same camera, while the SPN of any two cameras are totally independent. Common application of SPN includes source camera identification[4, 1, 2, 5, 6], image tampering detection[4, 1, 7, 2], and photographing year estimation[8].

To obtain a "Good" SPN is crucial to the performance of those forensic methods that involved it[4, 1, 2, 5, 6]. A more precisely estimated SPN means the more accurate source camera identification[9, 10], smaller detectable local tampering area[4], and more resistant to anti-forensic operations[11]. So forensic experts hope to approach ground-truth SPN at any accuracy, and continuously pursue better SPN extraction methods[12, 9]. In fact, the estimation of SPN, or equally the sensor response non-uniformity calibration[13], is a longstanding problem possibly as old as digital imaging itself. The traditional solution is to use flat-fielding based camera calibration experiments, e.g. using dark frames or standard light boxes. However in the case of digital forensics, we need to deal with images from common consumer digital cameras whose output images are highly disturbed by the linear/nonlinear internal processing of the camera[14], such as CFA interpolation, tone mapping (gamma correction). Meanwhile, the majority of low-end consumer digital cameras only support JPEG output image format. Conventional flat fielding based camera calibration will encounter difficulty for the subtitle SPN has been removed unrecoverably by the lossy JPEG compression. Even with stock of such images, the estimation accuracy of an SPN cannot be further improved. All these factors make it more difficult than ever to reveal the ground-truth SPN of a digital camera.

Consequently, digital forensic experts turned to use cluttered natural images to reveal SPN[15, 4, 16]. In this circumstance, the randomness of natural scenes can prevent the subtitle SPN signal to be completely removed by JPEG compression and other harmful post-processings. Although the natural scene also "contaminated" the observation of the SPN, from a theoretically point of view, it is still possible to recover the SPN as long as we have a sufficient number of these images. Recently, researchers have proposed a multiple of these methods and their derived versions. For example, Lukas et.al[1] proposed an additive SPN model and extraction method, Chen et. al[2] proposed a multiplicative SPN model and a MLE extraction method, and their improved versions [12, 9, 17]. What these methods share in common is that their image data set is constituted by photos of natural scenes, and the SPN extraction algorithms work by denoising each individual image. This would be a labouring task when the forensic application requires highly accurate SPN, which demands a large image data set. Moreover, these processes are hard to repeat or standardized for officially using by an authority. So it is necessary to study on how to extract SPN when image set is very large.

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This involves the calculation efficiency, estimation accuracy of an SPN extraction algorithm. And also, we must find out an effective way to collect large scale image data set in reality.

In this work, we propose a novel experimental method to create large image data set by capturing noise images displayed on a high-definition monitor. It offers the forensic researcher a fast way to create a large image data set. And this process is easy to standardized and fully repeatable. Correspondingly, a highly efficient homomorphic based SPN extraction method is proposed to deal with large numbers of photos. Further derivations show that it is a statistical optimal solution for multiplicative SPN estimation. In the experiment part, a comparative study is given on the proposed method and a prior state-of-art. Experimental results confirm the superiority of our method.

2. PROPOSED METHOD

In this section, we propose a novel experimental method to create large image data set efficiently, and then a computational efficient SPN extraction algorithm is proposed correspondingly. Figure 1 gives the overview of the processing pipeline of our method.

2.1. Create Large Image Data Set by Taking Photos of Onscreen Noise Images

Existing SPN extraction methods are all based on natural scene image data sets [18, 4]. In order to obtain a large non-repetitive image data set, a photographer have to replace his photographing scene randomly and constantly which is a labouring and time-consuming task in practice. Moreover, these steps can hardly be reproduced at elsewhere, thus various testing standards of SPN-based forensic method cannot be unified. Therefore, new experiment methods need to be developed for overcoming these barriers.

In this section, we propose a novel experimental method to collect hundreds of images in a few minutes. The experiment is carried out in a dark room with no interference of other illuminations. We display one random noise image at each time with a high resolution monitor, and use a digital camera (to be tested) to take photos on such images. All random noises should obey the same distribution with specified mean and variance, e.g. a uniform distribution used here. The position of the camera is fixed during the experiment using a tripod. The camera viewfinding scope should not exceed the screen border. The screen resolution is higher the better, so as to guarantee the randomness of each pixel photographed. While pressing camera shutter each time, a different random noise image will be displayed. The above process is repeated until the image number meets the SPN extraction accuracy requirement.

The prominent advantage of this method is that it can greatly accelerate the creation process of image data set, usually obtaining hundreds of noise image at about 10 minutes. Moreover, the automation of this photographing process can be achieved through designing camera control equipments or software, so that researchers can get photos of any number, thus the real value of SPN can be approached at high accuracy. Forensic experts can repeat the results of the SPN extraction experiment at any place through standardized experiment environment. This is conducive to unify the test parameter of passive forensic method, for example, the results of source identification or tampering detection will not differ due to the geographical location of testing laboratory.

2.2. SPN Extraction Based on Homomorphic Filtering

Different assumptions to SPN had resulted in two types of SPN extraction methods . One is based on the additive SPN model or the so called “fixed pattern noise”[1], while another is based on the PRNU(Photo Response Non-uniformity) noise which is a multiplicative SPN model[2]. But with the technical advancement of digital camera in recent years, the post-processing process within the camera usually eliminates the influence of additive SPN by adopting dark-frame removal method. The so called “dark frame” means a noise image captured in shutter closed status with the same camera configurations right after photographing a natural scene image. Through subtracting this frame, the influence of additive SPN can be eliminated. Therefore, forensic research is inclined to extract PRNU noise as sensor pattern noise. And the most famous forensic PRNU noise estimation algorithm is proposed by Chen et. al[2].

In this section, we proposed a new PRNU noise extraction algorithm based on homomorphic filtering. Compared with the method in [2], it is simpler, faster, and with justifiable optimality. It consists of three steps: 1) all natural images are superposed together to get one average image; 2) the logarithm on each pixel of average image; 3) extract PRNU by denoising algorithm. The advantage of this algorithm is that it only needs to denoise one image, while the algorithm in the past needs to carry out denoising for each image (N times). Meanwhile, it can be proved that when K is a white Gaussian noise(WGN), Wiener filter is a near-optimal solution when the image number N tends to infinite. The derivation is as follows:

We take the same image model used in [18] which is proposed by Healey et. al[13]. Then a color value of camera captured image is described as:

$$I(x,y) = g^{\gamma}[(1+K(x,y))Y(x,y)+\Theta_n(x,y)]^{\gamma}+\Theta_q(x,y) \quad (1)$$

This model considered the main processing procedures within a digital camera, including white balancing, tone mapping, additive and multiplicative sensor noise , and JPEG compression noise. g is the color channel gain factor caused by white balancing, its value is different with each photo according to the scene. Non-linear tone mapping is approximated by

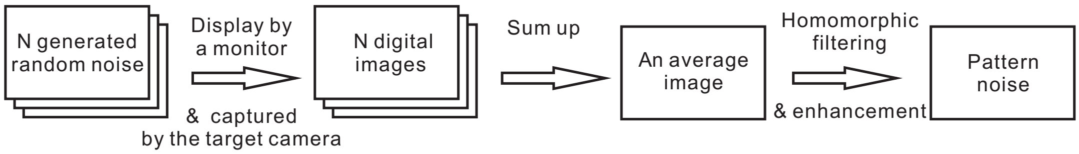

Fig. 1: Process of creating large image data set from random noise images.

Gamma transformation, with γ as Gamma correction factor. K is the PRNU noise to be extracted as SPN[2] . Θ_q is the JPEG quantization noise. Θ_n is other additive random noise, such as shut noise, dark current, and read out noise. The range scope of both $I(x,y)$ and $Y(x,y)$ are $[0,1]$. For concise purpose, (x,y) will be omitted in the following formulas, and $I(x,y)$ shall be expressed by I. Other 2-D signals shall be done in the same manner.

By overlaying all images in image set, we have

$$\frac{1}{N}\sum_{i=1}^{N} I_i = \frac{1}{N}\left\{\sum_{i=1}^{N} g_i^{\gamma}[(1+K)Y_i+\Theta_{n,i}]^{\gamma}+\sum_{i=1}^{N}\Theta_{q,i}\right\} \quad (2)$$

Carry out Taylor expansion to Eq. (2),

$$\frac{1}{N}\sum_{i=1}^{N} I_i = \frac{1}{N}[\sum_{i=1}^{N} g_i^{\gamma}Y_i^{\gamma}(1+\gamma K)+\sum_{i=1}^{N}\gamma Y_i^{\gamma-1}\Theta_{n,i}+\sum_{i=1}^{N}\Theta_{q,i}] \quad (3)$$

In Eq. (3), noise $\Theta_{n,i}$ can be ignored as compared to image irradiance $Y_i^{\gamma-1}$. Meanwhile, when N is large enough, $\sum_{i=1}^{N}\Theta_{q,i}$ can also be ignored. Then Eq. (3) is simplified as,

$$\frac{1}{N}\sum_{i=1}^{N} I_i \approx \frac{1}{N}(1+\gamma K)\sum_{i=1}^{N} g_i^{\gamma}Y_i^{\gamma} \quad (4)$$

Taking logarithm and carrying out Maclaurin expansion,

$$Ln(\frac{1}{N}\sum_{i=1}^{N} I_i) \approx -LnN + Ln(1+\gamma K)+Ln(\sum_{i=1}^{N} g_i^{\gamma}Y_i^{\gamma}) \quad (5)$$

$$\approx -LnN+\gamma K+\mathcal{O}(\gamma^2K^2)+Ln(\sum_{i=1}^{N} g_i^{\gamma}Y_i^{\gamma}) \quad (6)$$

With adequate production quality control, a sensor chip's PRNU noise should be bounded. Typically, the value of K is restricted in $[-0.5,0.5]$ and $\gamma\approx 0.5$. So the higher order term $\mathcal{O}\left(\gamma^2K^2\right)$ can be ignored. Thus a first-order approximation for Eq.(6) would be adequate. Moreover, when N tends to be infinite, we have

$$\lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N} g_i^{\gamma}Y_i^{\gamma} = E\left[g_i^{\gamma}Y_i^{\gamma}\right] = E[g_i]^{\gamma}E[Y_i]^{\gamma} \quad (7)$$

Of which, we suppose the image irradiance Y_i and color channel gain factor g_i are mutually independent. For the random noise images are generated with a constant mean, and g_i is a global variable independent of pixel location (x,y) within each image, then

$$E[g_i]^{\gamma}E[Y_i]^{\gamma} = C \quad (8)$$

where C is a constant independent of pixel location (x,y).

Bringing Eq. (6) and Eq. (8) together, we can forecast that when N tends to be infinite, K(with a scaling factor γ) can be obtained simply by eliminating the DC part of the average image. In practice, when the condition is not very ideal, Eq. (8) will not hold strictly. Nevertheless, taking consideration of the linear manipulations in the digital imaging process, such as point spread function, interpolation algorithm of decoding mosaic, we can still suppose that $Ln(\sum_{i=1}^{N} g_i^{\gamma}Y_i^{\gamma})$ can be modeled locally as the auto-regressive and moving average (ARMA) model. Then when K is assumed to be a stationary ergodic noise, specifically the WGN, then the optimal estimation of K can be obtained through applying locally the 2-D Wiener filter $\mathcal{F}_{wiener2}(\cdot)$:

$$\hat{K} = \frac{1}{\gamma}[Ln\sum_{i=1}^{N} I_i - \mathcal{F}_{wiener2}(Ln\sum_{i=1}^{N} I_i)] \quad (9)$$

In practice, Eq. (9) is a *near-optimal* estimation of PRNU, since the higher order term $\mathcal{O}\left(\gamma^2K^2\right)$ is ommitted in the derivation.

This solution is different from most existing SPN extraction methods [15, 19, 1, 4, 12, 20, 18, 2, 21, 10, 9], which works by denoise each individual photo. It only needs to denoise one image, e.g. the logarithm of the average image, for each SPN extraction. Meanwhile, the optimal choice of denoising filter in this solution is always determined, so one will not waste any time on finding a "good" denoising filter among a dozen of existed ones as to adapt Ad-Hoc experimental circumstances. The principles derived above can guarantee that it works to a certain degree even in the worst case.

3. EXPERIMENTAL RESULTS

As mentioned in Section 1, the ground-truth SPN of a common consumer digital camera is hard to obtain in practice, existing methods [15, 19, 1, 4, 12, 20, 18, 2, 21, 10, 9] often use the results of source camera identification test as the indirect measurement of SPN extraction effectiveness. The essence of source camera identification test is to use the SPN $\hat{\mathbf{K}}$ obtained from an inspected camera to carry out signal detection on the weak SPN signal $\mathbf{K}$ contained in a testing image $\mathbf{I}_i$. According to [18], the optimal detector of PRNU noise $\mathbf{K}$ is

$$NCC\left(\hat{\mathbf{K}}\mathbf{I}_i,\mathbf{W}_i\right) = \frac{\sum_x\sum_y \hat{K}(x,y)\,I_i(x,y)\,W_i(x,y)}{\sqrt{\sum_x\sum_y I_i(x,y)\,\hat{K}(x,y)^2\cdot\sum_x\sum_y W_i(x,y)^2}} \quad (10)$$

where $\hat{\mathbf{K}}\mathbf{I}_i$ means the element-wise multiplication of two matrices $\hat{\mathbf{K}}$ and $\mathbf{I}_i$. $\mathbf{W}_i$ is the noise residual obtained by denoising $\mathbf{I}_i$. The identification performance of $\hat{\mathbf{K}}$ can then be revealed by evaluating Eq. (10) with a large collection of testing images from both the inspected camera and many other cameras and draw an ROC curve.

Here we compared the source camera identification performance of the PRNU noise obtained with the proposed algorithm and the algorithm proposed in [2]. The experiment involved four patterns of digital camera, say Canon PowerShot A610, Canon PowerShot A650, Nikon D300, Sony DSC T77. Each camera is used to obtain an SPN extraction image data set and a natural scene image data set for testing. Each data set contains 200 JPEG images and only the 128x128 center block of the green channel of each image is used in the experiment.[1] The PRNU noise extraction image data sets are obtained with our proposed experiment method addressed in Section 2.1. And the natural scene image data sets contain randomly photographed indoor/outdoor scenes. Following the settings in [18], the noise residual $\mathbf{W}_i$ and PRNU noise $\hat{\mathbf{K}}$ used the same denoising filter which is the wiener2 filter in Matlab.

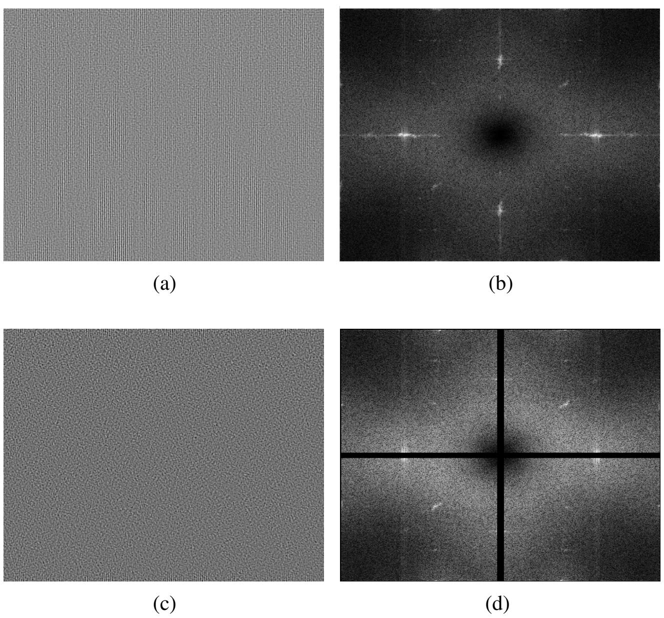

Fig. 2: PRNU noise enhancement. (a) and (c) is the PRNU noise before and after the enhancement; (c) and (d) are the magnitude spectrums of (a) and (c) respectively.

The extracted "original" PRNU noise needs to be further enhanced [15, 18, 9], so as to restrain the cyclical peak in SPN magnitude spectrum caused by color filter, JPEG blocking effects, screen cyclical structure and the shock in photographing. Meanwhile, screen warping and hand-shaking can cause strong interference in horizontal and vertical direction. As shown in Fig. 2, the influence of such interference factors can be restrained by setting the magnitude spectrum of these frequency components as zero.

[1]ROC curves for larger image blocks(e.g. 1024x1024) are visually akin to "right angle"s, despite their extraction method. Then hardly any difference can be observed from their plots.

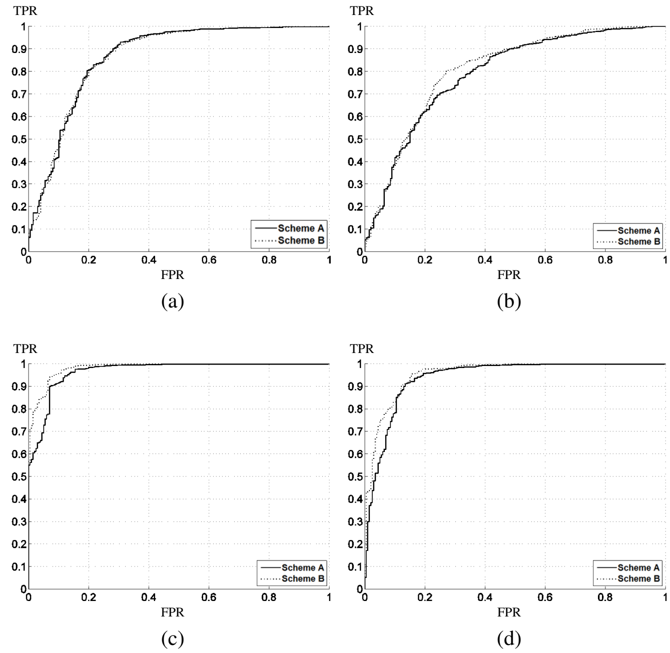

Fig. 3: Source identification ROC curve comparison of the proposed and the reference method[2]. (a) Nikon D300; (b) Canon 610; (c) Sony T77; (d) Canon 650. The reference method is denoted as Scheme A, while the proposed method is Scheme B. The horizontal and vertical axies are the False Positive Rate(FPR) and True Positive Rate(TPR) respectively.

Figure 3 shows the ROC curves obtained from the proposed and the reference method. Of which, the ROC performance of the proposed method in Fig.3b, 3c, 3d has been improved as compared with the reference method, while in Fig. 3a they are at least identical.

4. CONCLUSION

In this work, we considered the problem of extracting forensic SPN from very large image data set and proposed a solution which is made up by an experimental and an algorithmic methodologies. The resulted solution is a trade-off between computational efficiency, theoretical optimality, and experimental repeatability. These efforts might help to standardize the SPN extraction procedures and performance evaluation for its future applications on formal occasions.

The proposed methodologies also have certain limits. For example, the experimental configurations will inevitablely affect the PRNU estimation accuracy in some degree. Moreover, when the image number N is not significantly large, e.g. $N \leq 20$, the derivations in Section 2.2 will no longer be valid. Consequently , the estimation of PRNU will deteriorate which might induce an inferior source identification performance, compared with the reference method[2]. Meanwhile, due to the limited space, some important issues are not described in details or discussed extensively here. For example, the detailed settings of the proposed experimental methodology; How would the proposed algorithm behave on large nature image data set? These will be addressed in our future works.

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