Decomposed Photo Response Non-Uniformity for Digital Forensic Analysis

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Abstract. The last few years have seen the applications of Photo Response Non-Uniformity noise (PRNU) - a unique stochastic fingerprint of image sensors, to various types of digital forensic investigations such as source device identification and integrity verification. In this work we proposed a new way of extracting PRNU noise pattern, called Decomposed PRNU (DPRNU), by exploiting the difference between the *physical* and *artificial* color components of the photos taken by digital cameras that use a Color Filter Array for interpolating *artificial* components from *physical* ones. Experimental results presented in this work have shown the superiority of the proposed DPRNU to the commonly used version. We also proposed a new performance metrics, Corrected Positive Rate (CPR) to evaluate the performance of the common PRNU and the proposed DPRNU.

Keywords: Digital forensics, PRNU noise pattern, integrity verification, source device identification.

1 Introduction

Among many areas of non-intrusive forensic analysis, extracting and examining the Photo Response Non-Uniformity noise pattern (PRNU), which is a unique fingerprint of image sensors, is one of the most effective methods for digital forensic analysis. As a signature of digital cameras, a PRNU noise pattern is applicable to digital forensic areas such as source device identification [1, 2] and integrity verification [3]. The basic idea of using the PRNU noise pattern for identifying source devices is as follows. Firstly, the PRNU noise patterns of imaging devices, e.g., digital cameras, are extracted from a number of low-contrast images and then the average of them are calculated to serve as the reference fingerprints of the devices. Secondly, the PRNU of the image under investigation is extracted and compared against the reference fingerprint of each device available to the investigator in hope that it would match one of the reference fingerprints, thus identifying the source device that has taken the target image [1, 2]. For integrity verification, a window is slid across the image, and the PRNU noise from the area covered by the window is compared to the corresponding PRNU block of a reference fingerprint. An authentic block covered by the window is expected to have higher correlation with the reference PRNU block while a forged block should have lower correlation [3].

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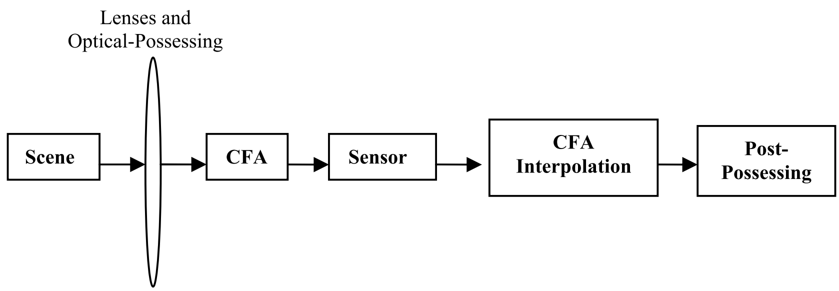
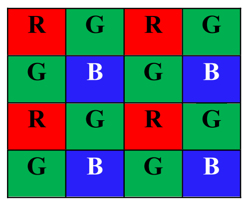


(a)



(b)

Fig. 1. The processing inside the digital camera, and the typical Bayer CFA. a) The process of capturing a digital. b) Bayer CFA, a typical Color Filer Array.

According to these descriptions, we know that the effectiveness of the aforementioned methods is based on the quality of the PRNU noise. The method for extraction the PRNU noise extraction proposed in [1 – 3]

$$PRNU(i,j) = I(i,j) - I'(i,j) \tag{1}$$

where $I(i,j)$ is the intensity of pixel (i,j) and $I'(i,j)$ is the intensity of pixel (i,j) in the denoised (low-pass filtered) version of $I(i,j)$. In [1 - 3], the entire filtered noise pattern is treated as the PRNU noise pattern. The PRNU maybe caused either by optical lenses non-uniformity, optical filtering, or by the digital post-processing algorithms. Moreover, details from the scene as well as the noise introduced at the acquisition and storage phases may contribute to the left hand side of Eq. (1).

Another factor worth investigating is the use Color Filter Array (CFA) in most digital cameras. During the image acquisition process of a typical digital camera as illustrated in Fig. 1(a), not every color component of each pixel is physically captured. Instead, for each pixel, only one color component is acquired, depending on a 2 × 2 coordinate pattern – the CFA, as illustrated in Fig. 1(b), pre-defined by the manufacturer. Later an Interpolation Matrix (IM) is utilized to interpolate the missing color components by involving the neighboring pixels according to the CFA [4, 6, 7]. Throughout the rest of this work, we will use the term *physical component* for the color channel/component of each pixel with the same color as that of the corresponding element of the CFA and *artificial component* for the other two color channels/components. Because the *artificial* colors obtained through the interpolation operation is not directly acquired from the scene by *physical* hardware, we expect that the

PRNU noise pattern extracted from the physical components, which are free from interpolation noise, should be more reliable than that from the artificial channels, which carry interpolation noise. Based on this assumption we propose an improved Decomposed PRNU extraction method, which first decomposes each color channel into 4 sub-images and then extracts the PRNU noise from each sub-image. The PRNU noise patterns of the sub-images are then assembled to get the complete Decomposed PRNU (DPRNU).

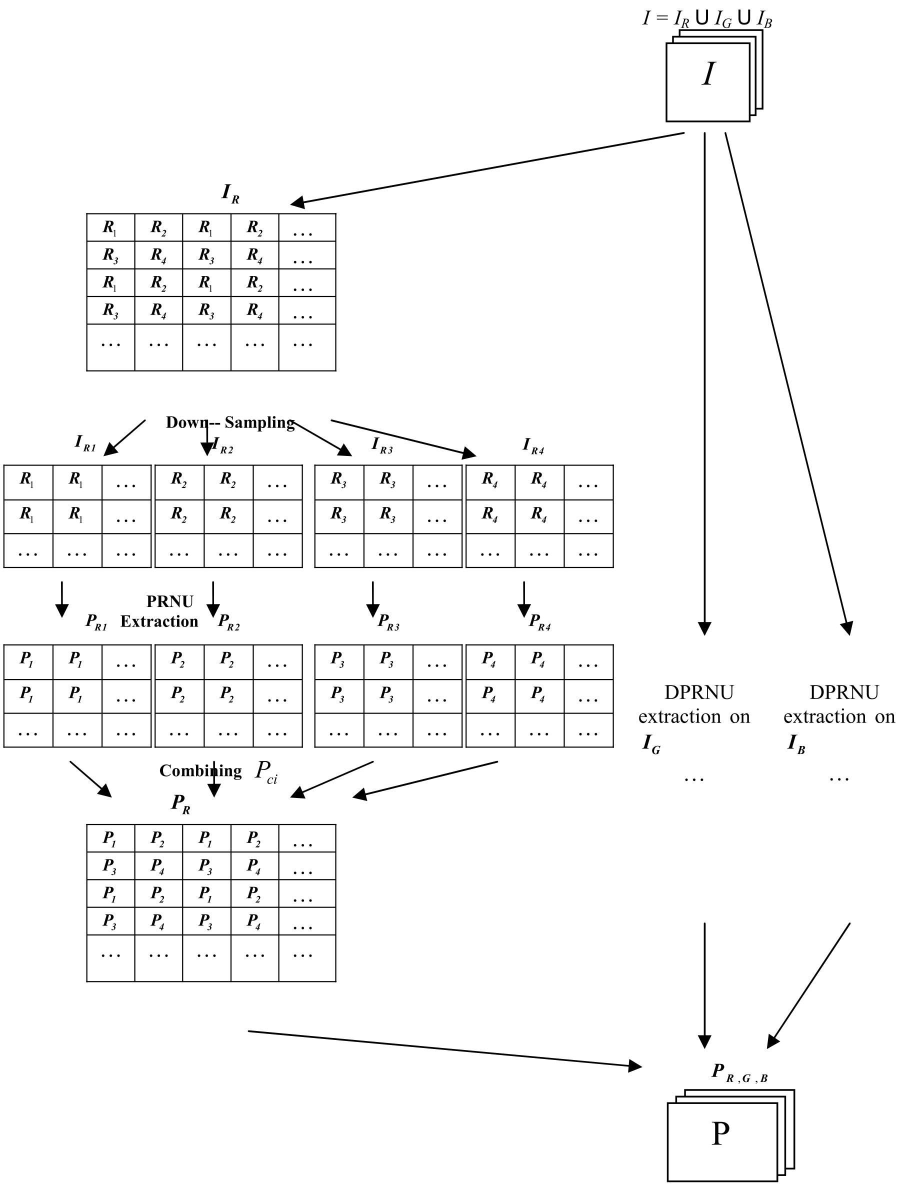


Fig. 2. The framework of the Decomposed PRNU extraction

2 Proposed Decomposed PRNU (DPRNU)

As illustrated in Fig. 2, to extract the DPRNU, we first separate the three color channels I_c, $c \in \{R, G, B\}$ of a color image I. Since a CFA consists of repeating patterns of 2 × 2 pixels as shown in Fig. 1(b) and we know that, for each pixel at the same coordinates of I, only one of the three color components is *physical* and the other two are *artificial*, so the second step is, for each channel I_c, we perform 2:1 down-sampling across both horizontal and vertical dimensions to get four sub-images, I_{ci}, $i \in \{1, 2, 3, 4\}$. A PRNU noise pattern, P_{ci}, is then extracted from each sub-images I_{ci}. Finally the PRNU noise pattern P_c of each channel is formed by combining the four sub-PRNU noise patterns P_{ci}, $i \in \{1, 2, 3, 4\}$. The advantage of the proposed method is that when the PRNU noise patterns of images taken by different cameras with different CFA, the dissimilarity would be enhanced when physical components are compared against artificial components, thus improving performance.

3 Experiments

Fig 3(a) shows a photo of 640 × 480 pixels captured by Olympus C730 and Fig 3(b) is a forged image with the can removed. Fig 3(c) is another forged image with an added can. We use the Haar wavelet and the Wiener filter [5] to perform low-pass filtering in the wavelet domain when extracting PRNU. Both the traditional PRNU [1 – 3] and the proposed DPRNU of the images are extracted and compared block by block as a window of 128 × 128 pixels is slid across the images in a 10-pixel-wide step. We use the commonly adopted True Positive (TP), True Negative (TN), False.

Positive (FP) and False Negative (FN) defined in Eq. (2) – (5) as metrics to evaluate the performance of the two types of PRNU noise patterns.

$$True\ Positive\ Rate\,(TP) = \frac{Number\ of\ True\ Positive}{Total\ Number\ of\ Positive\ Instances} \tag{2}$$

$$True\ Negative\ Rate\,(TN) = \frac{Number\ of\ True\ Negative}{Total\ Number\ of\ Negative\ Instances} \tag{3}$$

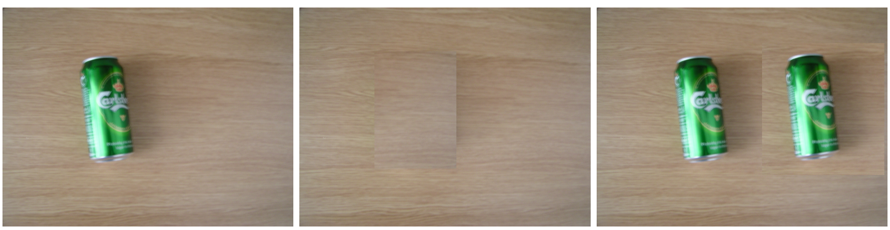
$$False\ Positive\ Rate\,(FP) = \frac{Number\ of\ False\ Positive}{Total\ Number\ of\ Positive\ Instances} \tag{4}$$

$$False\ Negative\ Rate\,(FN) = \frac{Number\ of\ False\ Negative}{Total\ Number\ of\ Negative\ Instances} \tag{5}$$

We use correlation between PRNU noise patterns as the similarity metrics. After the correlations between all pairs of PRNU blocks have been calculated, we deem a block with a PRNU correlation lower than α times of the standard deviation (STD) as forged. We can see from Eq. (2) – (5) that because the denominators are always fixed because they are "ground truth", when the value of α is changed, the numerators may change significantly, making these four metrics less reliable. Therefore, we propose another metrics called *Corrected Positive Rate* (CPR), to measure the fraction of True Positives of the total number of the *detected* Positive instances.

$$\textit{Corrected Positive Rate}\,(\mathrm{CPR}) = \frac{\textit{True Positive}}{\textit{Number of Detected Positive Instances}} \tag{6}$$

When α is greater, less forged blocks will be detected because the threshold for a block to be deemed as forged is lower. That is to say that the detected positives are more likely to be true positives and the number of false reports would become lower. So from Eq. (6) we can see that the value of CPR at greater value of α would be more reliable. We use three different values of α, 1, 1.5 and 2, in our experiments. Table 1 shows the results associated with different values of α. The reader is reminded that according to Eq. (2) – (6), high values of TP, TN and CPR and low values of FP and FN suggest greater performance. We tabulate the performance metrics when the forged images of Fig. 3(b) and 3(c) are tested in Table 1 and 2, respectively. We can see from these two tables that, although for most cases, the proposed DPRNU outperforms the common PRNU in terms of the first 4 metrics (TP, TN, FP and FN), these four metrics do not always reveal the performance difference at different values of α because many differences are marginal. This situation conforms to our concern about the reliability of these four metrics. On the other hand, when α equals 2, the



(a) (b) (c)

Fig. 3. Experimental images of forge detection (image size is 640 × 480). a) The original image, b) The image forged by the removing attacking, c) The image forged by the copy-pasted attacking.

Table 1. Experimental results when the forged image of Fig. 3(b) is tested

α	Noise pattern	TP	TN	FP	FN	**CPR**
2	PRNU	0.0077	0.9467	0.0533	0.9923	**0.0459**
	DPRNU	0.0908	0.9476	0.0524	0.9092	**0.3717**
1.5	PRNU	0.1701	0.8541	0.1459	0.8299	0.2848
	DPRNU	0.1944	0.8939	0.1061	0.8056	0.3848
1	PRNU	0.3529	0.7699	0.2301	0.6471	0.3437
	DPRNU	0.3657	0.7590	0.2410	0.6343	0.3413

Table 2. Experimental results when the forged image of Fig. 3(c) is tested

α	Noise Pattern	TP	TN	FP	FN	**CPR**
2	PRNU	0.0907	0.9433	0.0567	0.9093	**0.2211**
	DPRNU	0.1274	0.9716	0.0284	0.8726	**0.4436**
1.5	PRNU	0.2592	0.8750	0.1250	0.7408	0.2691
	DPRNU	0.2743	0.8574	0.1426	0.7257	0.2545
1	PRNU	0.5313	0.7831	0.2169	0.4687	0.3030
	DPRNU	0.4730	0.7007	0.2993	0.5270	0.2190

proposed metrics CPR (Eq. (6)) clearly indicates the superiority of our proposed DPRNU. However, when α is at lower levels (1 and 1.5), even CPR cannot always provide clear evidence about which types of PRNU is a better candidates. This conforms to our earlier statement that the value of CPR at greater value of α is more capable of providing reliable evaluation.

4 Conclusion

In this work we have briefly reviewed the use of PRNU noise pattern in source camera identification and integrity verification and the role of CFA in the image acquisition process of digital cameras. We then proposed a new way of extracting PRNU noise pattern, called Decomposed PRNU (DPRNU) by exploiting the difference between *physical* and *artificial* components. We also proposed a new performance metrics, Corrected Positive Rate (CPR) to evaluate the performance of the common PRNU and the proposed DPRNU. The experimental results presented in this work have shown the superiority of the proposed DPRNU.

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