# DIGITAL CAMERA IDENTIFICATION BASED ON CURVELET TRANSFORM

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**ABSTRACT**

In this paper, A new method is proposed for digital camera identification from its color images using image sensor noise. Currently the proposed camera identification methods use wavelet-based denoising filter to extract the sensor noise feature. However, the wavelet methods may smooth the edged while denoising and this will lead to low accuracy for those images including highly textured regions. In order to overcome some inherent limitations of wavelet transform, we use curvelet-based denoising filter to obtain the camera fingerprint. Experimental results show that this method provides higher accuracy than other methods on the condition of using a few color images to compute reference pattern, especially for those color images including highly textured regions.

***Index Terms***— Multimedia forensics, camera identification, image sensor noise, curvelet transform

## 1. INTRODUCTION

During the past decade, digital images continue to replace its analog counterpart. Sophisticated and low-cost photoediting software tools have become affordable and available to a large number of people. The advanced digital image processing techniques provided by the image editing software like Adobe Photoshop or Gimp make it easy to create, edit and manipulate digital images without leaving any obvious traces of having been modified. Lately discovered forgeries in newspapers and scientific journals are only the tip of the iceberg. Particular attention has to be drawn to courtroom applications, in which the authenticity of photographs as pieces of evidence deserves utmost importance.

Recently, methods subsumed to the concept of multimedia forensics have been proposed to address these issues. There are two main branches, namely source identification and forgery detection[1]. Source identification focuses on identifying the source digital devices (cameras, mobile phones, camcorders, etc) using the media produced by them, while forgery detection attempts to discover traces of tampering in the digital media (audio clips, video clips, images, etc). In this research, we focused on source digital camera identification and propose a new method to identify the camera "fingerprint".

In fact, there have been some methods to identify the source digital camera. Kharrazi et al.[2] proposed a method for source camera identification based on supervised learning. The correct classification ranged from roughly 78% for the worst case to 95% in the best case. Luk$\acute{a}\check{s}$ et al.[3] first proposed to use sensor noise for digital camera identification. Their method has a higher accuracy than the supervised learning method. In their method, they determine each camera's reference pattern noise, which serves as a unique identification fingerprint. Mo Chen et al.[4] consider the identification task as a joint estimation and detection problem, they use a simplified model for the sensor output and then derive a Maximum Likelihood estimator of the PRNU. The two methods in [3, 4] use the wavelet-based denoising filter. But wavelet transform is only optimum for point-singularities and is less efficient for line-singularities or curve-singularities. Therefore if an image includes highly textured regions, wavelet-based denoising filter will introduce some traces in those regions. In fact, these traces does not exist. These traces will decrease the accuracy of camera identification.

In this paper, we extend the sensor pattern noise camera identification for grayscale image to color image. We first capture the noise of color images from the same digital camera using a curvelet-based denoising filter by subtracting a denoised version of each color channel of the image from each color channel of the original image. The remaining noise contains information about imperfections in the sensor. For a given color image, we calculate the correlation coefficient between the color image noise and the reference pattern. Then we can use this correlation to determine whether the color image was taken by the camera or not. This method only need several color images for the computation of noise reference pattern. So this method provides a higher identification speed and better identification accuracy for a color image.

## 2. IMAGE SENSORS NOISE

Sensor noise is inherently present in each image captured with a digital camera. Noise in image sensors is typically separated into two categories: random noise and pattern noise[5]. Random noise is temporally random, and it is not constant from frame to frame in the image. Pattern noise does not change significantly from frame to frame. Pattern noise is divided into two components: fixed pattern noise(FPN) and photo-response non-uniformity(PRNU). PRNU is defined as different sensitivity of pixels to light caused by the inhomogenity of silicon wafers and imperfections during the sensor manufacturing process. This feature of the PRNU noise make it as an unique label for a image sensor, even the same type sensor coming from the same manufacture would have an unique feature. Contrary to random noise, PRNU noise is relatively stable between images, therefore it can be used for camera identification. so all images acquired with the same image input device contain a similar spatial noise pattern, which Luk$\acute{a}\check{s}$ and Fridrich et al. [3] assume to be unique for each image sensor. This PRNU noise can be modeled as white Gaussian noise(WGN) with variance $\sigma_0^2$.

## 3. CAMERA FINGERPRINT IDENTIFICATION

### 3.1. Curvelet Transform

The Continuous Curvelet Transform has gone through two major revisions. The first generation of curvelet transform[6] used a complex series of steps involving the ridgelet analysis of the radon transform of an image. The second-generation curvelet transform discarded the use of the ridgelet transform, thus reducing the amount of redundancy in the transform and increasing the speed considerably.

Curvelet transform has several digital implementations. The two most recent ones are introduced in[7]. The first method is the Unequispaced FFT Transform, where the curvelet coefficients are found by irregularly sampling the Fourier coefficients of an image. The second method is based on the wrapping of specially selected Fourier samples. We will use the latter throughout this paper. However, the use of the USFFT-based digital curvelet transform would have the same output.

### 3.2. Identification based on Curvelet Transform

In method[3], Luk$\acute{a}\check{s}$ et al. use wavelet-based method to identify the source digital camera fingerprint. But in our method, we use curvelet-based method to identify digital camera fingerprint. This method overcomes the limitation of wavelet-bases method. In order to identify a given color image $\mathcal{I}$ was taken with camera $\mathcal{C}$, we first determine the camera noise reference pattern $\mathcal{R}_\mathcal{C}$, which is an approximation to the PRNU noise. The noise reference pattern $\mathcal{R}_\mathcal{C}$ is a camera-specific fingerprint.

Because only Digital Single Lens Reflex(DLSR) camera can access the raw sensor output, and most consumer cameras do not allow access to the raw sensor output, it is generally not possible to extract the PRNU noise using flat fielding method. But we can obtain an approximation to the PRNU noise by averaging multiple images $\mathcal{I}_s$, $s = 1, \ldots, S$. In order to get the approximation of PRNU noise, we using a curvelet-based denoising filter $\mathcal{F}$.

We can use the method in section 3.1 to calculate the curvelet coefficients and then use the hard-thresholding rule for estimating unknown curvelet coefficients. Although the method of curvelet-based filtering overcomes the limitation of wavelet-based method, the curvelet-based method exhibits visual artifacts know as pseudo-Gibbs phenomena. Therefore, Donoho et al.[8] proposed a translation invariant denoising method, also known as cycle spinninig, to supress such artifacts by averaging over the denoised signals of all circular shifts. Therefore, we combine curvelet transform and cycle spinning as the curvelet-based denoising filter $\mathcal{F}$. One can apply the following procedure to get the denoised version of a color image. We first cycle spin the color image $\mathcal{I}$ with once translation in 2D directions. Then we apply curvelet transform to the translated color image and get the curvelet coefficients $c(j, \ell, k)$ at all scales and directions. Here we let scale $j = log_2(512) - 3$, angle parameter $\ell = 16$. Then we use the following hard-thresholding rule for estimating the unknown curvelet coefficients $\hat{c}(j, \ell, k)$:

$$\hat{c}(j,\ell,k) = \begin{cases} c(j,\ell,k), & if c(j,\ell,k) \geq k \cdot \sigma_0 \cdot \tilde{\sigma} \\ 0, & if c(j,\ell,k) < k \cdot \sigma_0 \cdot \tilde{\sigma} \end{cases} \tag{1}$$

where let $k = 2.2$ for scales except finest and let $k = 2.5$ for finest scale. $\tilde{\sigma}$ can be obtained according to the method in [9]. Then we apply the inverse curvelet transform to $\hat{c}(j, \ell, k)$ and obtain the denoised image. Finally, we apply inverse cycle spinning to the denoised image and get the final result $\mathcal{F}(\mathcal{I}_s)$. The noise image can be obtained by the following equation:

$$\mathbf{n}_s = \mathcal{I}_s - \mathcal{F}(\mathcal{I}_s) \tag{2}$$

In the process of denoising, image $\mathcal{I}_s$ is divided to $512 \times 512$ image blocks. Each image block is denoised for each color channel separately. In [3], author suggest the number of images $S > 50$. In fact, the author in [3] use local adaptive shrinkage wavelet to extract the camera fingerprint, this method is computational intensive. In our method, because we use hard-thresholding rule for estimating the denoised curvelet coefficients, the computing time is reduced considerably. Although we only use 20 images to get the noise reference pattern $\mathcal{R}_\mathcal{C}$, our method still can identify the source camera with a higher accuracy by using the noise reference pattern $\mathcal{R}_\mathcal{C}$.

We select 20 images taken with camera $\mathcal{C}$ randomly. Then we use curvelet-based denoising filter to extract the noise $\mathbf{n}_i (i \in R, G, B)$ for each color channel, and average these noise in 3 color channels. So we get noise reference pattern $\mathcal{R}_\mathcal{C}$ of camera $\mathcal{C}$ respectively. The noise reference pattern includes 3 noise reference patterns $\mathcal{R}_{\mathcal{C}_\mathbf{R}}$, $\mathcal{R}_{\mathcal{C}_\mathbf{G}}$, $\mathcal{R}_{\mathcal{C}_\mathbf{B}}$ in 3 color channel. Then the 3 reference patterns are converted to 3 vectors. To decide whether a specific color image $\mathcal{I}$ was taken by camera $\mathcal{C}$, we calculate its noise in 3 color channels respectively. Then we compute 3 correlations $\rho_R, \rho_G, \rho_B$ between 3 reference patterns coming from 3 color channels and the noise coming from three 3 channels of this new image:

$$\rho_i(\mathcal{R}_{\mathcal{C}_i}, \mathbf{n}_i) = \frac{(\mathbf{n}_i - \bar{\mathbf{n}}_i) \cdot (\mathcal{R}_{\mathcal{C}_i} - \bar{\mathcal{R}}_{\mathcal{C}_i})}{\|\mathbf{n}_i - \bar{\mathbf{n}}_i\| \|\mathcal{R}_{\mathcal{C}_i} - \bar{\mathcal{R}}_{\mathcal{C}_i}\|} \tag{3}$$

where the bar above a symbol denotes the mean value, and $i \in R, G, B$. Then we compute the correlation $\rho_\mathcal{C}$ between noise reference pattern and a new color image by using $(\rho_R + \rho_G + \rho_B)/3$. Finally, we calculate the threshold $\theta_{\mathcal{C}}$ of each camera according to principle of minimizing the false rate. Let $\theta_{\mathcal{C}} = \rho'_{max} + \varepsilon$, where $\rho'_{max}$ is the maximum value for a specific image that was not taken by camera $\mathcal{C}$, and $\varepsilon$ is a small positive real number. This method of computing $\theta_{\mathcal{C}}$ can minimize the false acceptance rate(FAR). The value $\rho_{\mathcal{C}}(\mathcal{R}_{\mathcal{C}}, \mathbf{n})$ is then compared to the threshold $\theta_{\mathcal{C}}$ to reach the final decision.

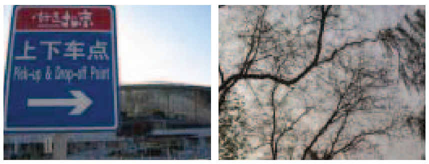


**Fig. 1**. Some images used in our experiments. There are not heavily textured regions in the left image, and the right image includes heavily textured regions

## 4. EXPERIMENTS

In this section, we use curvelet-based deniosing filter to obtain the noise reference pattern and apply the reference pattern to the identification of camera fingerprint. The program is written in python language and run in Ubuntu linux operation system. For our experiments, we prepared an image database containing approximately 200 images from each camera(Sony DSC-P8, Fujifilm FinePix F140 and Canon IXUS 700). The 200 images coming from a camera include 100 heavily textured images combined with very bright and dark areas and 100 images in which there is not heavily textured. The example of two class color images are shown in Figure 1. The reason we select heavily textured images as test data is that the method in [10] can't detect two heavily textured regions combined with very bright and dark areas. So the heavily textured images will give a better comparison. These 600 images were taken with and without the flash and with variant zoom settings and under vastly different ambient temperatures ranging from winter scenes taken at $-12\,^{\circ}$C to summer scenes taken at $30\,^{\circ}$C. Here we compare our method with the extended method from[3] which uses the wavelet-based denoising filter to extract noise and uses $(\rho_R + \rho_G + \rho_B)/3$ to compute the $\rho_{\mathcal{C}}$. The noise reference pattern of Sony DSC-P8 for extended method was obtained from 50 images taken with this camera. Then correlation $\rho_{\mathcal{C}}$ between the noise reference pattern of Sony camera with the noise of 600 images is computed. The left column in Figure 2 is the experimental result of the extended method from[3]. In our method, we select 20 images of natural scenes. Then we compute the noise reference pattern $\mathcal{R}_{\mathcal{C}}$. Finally, $\rho_{\mathcal{C}}$ is calculated. The right column in Figure 2 is the experimental result of our method. The correlation values in right figure of the first row of Figure 2 are greater than the correlation values in left figure of the first row of Figure 2, especially for those images including heavily textured regions combined with very bright and dark areas. The same process is applied to Fujifilm FinePix F410 and Canon IXUS 700. The second and the third row in Figure 2 show the experimental results. In order to show all points in a figure, we define $\rho_{max}$ and $\rho_{min}$. If $\rho_{\mathcal{C}} > \rho_{max}$, let $\rho_{\mathcal{C}} = \rho_{max} - 0.01$. If $\rho_{\mathcal{C}} < \rho_{min}$, let $\rho_{\mathcal{C}} = \rho_{min} + 0.01$. The results of Fujifilm shows the values of the correlation coefficients are larger than others. We can conclude that the sensor noise in Fujifilm F140 is more obvious than others. From Figure 2, we can conclude the two methods have the same accuracy rate for images in which there is no heavily textured part, but if the images include heavily textured part, the method that uses curvelet-based denoising filter has the better accuracy rate than the method that extends [3] from grayscale image to color image. In forensic practical application, it is important to keep the false acceptance rate (FAR) low. We can use Neyman-Pearson method to calculate a threshold that make the false rejection rate (FRR) minimize while imposing a bound on the FAR. But in order to compare the two method, we compute the FRR value on the condition of FAR$= 0$. The result of FRR value of the two method are shown in Table 1. From Table 1, we can conclude the our method can give higher accuracy of identification than the extended method from [3], and our method only use 20 color images to calculate the noise reference pattern.

| Method | Sony | Fujifilm | Canon |
|---|---|---|---|
| Wavelet-based method | 18% | 0.5% | 35.5% |
| Curvelet-based method | 11% | 0% | 10% |

**Table 1**. The false rejection rate(FRR) of the two method

## 5. CONCLUSION

In this paper, we propose a new method to the problem of camera identification from color images. The proposed identification technique based on curvelet transform was tested on 600 color images obtained from three digital cameras. The experiment results show curvelet-based denoising filter is better than wavelet-based denoising filter for the camera identification.

## 6. REFERENCES

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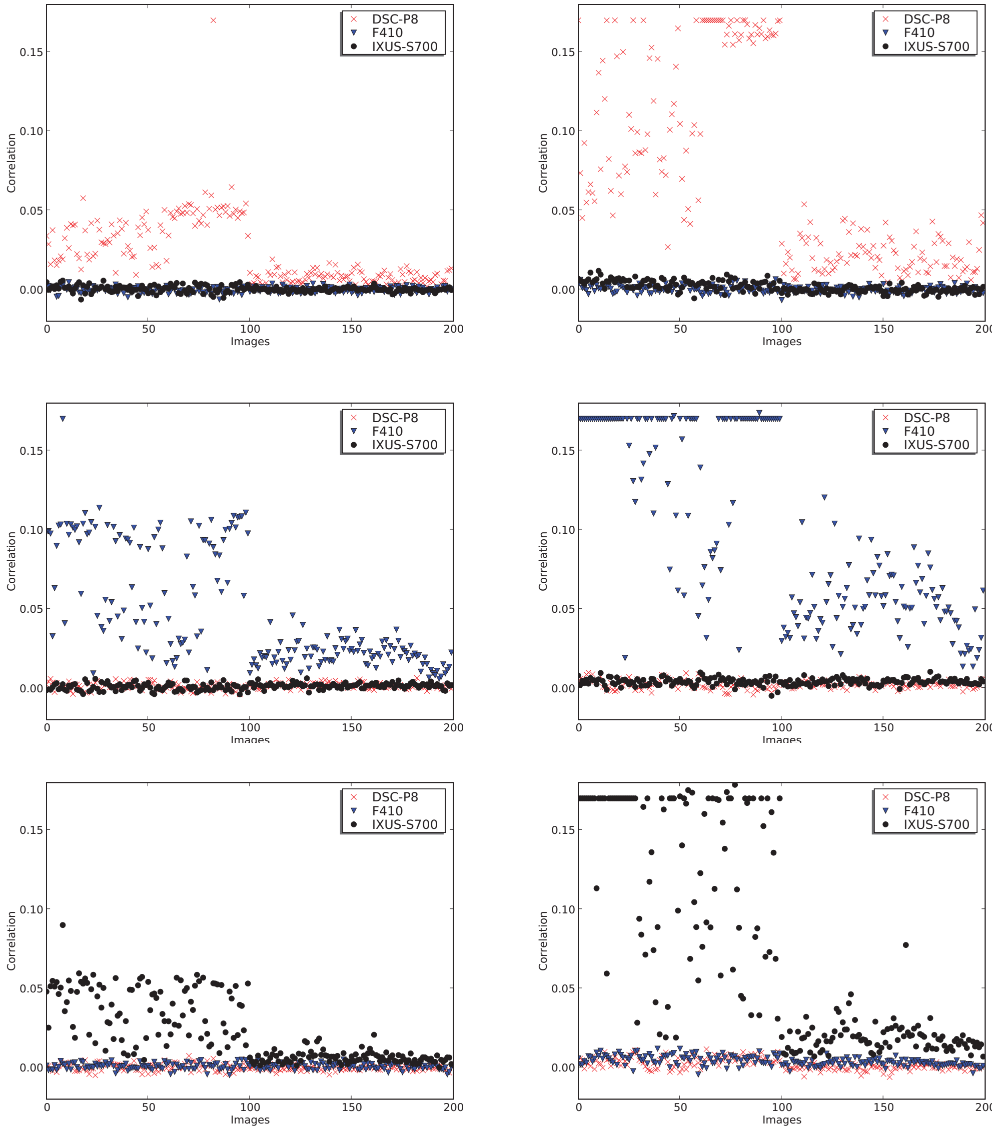


**Fig. 2**. The first row shows the two methods' correlation $\rho_C$ between the noise from color images captured with the three cameras and the reference pattern of Sony DSC-P8. The second row shows the correlation $\rho_C$ between the noise from color images captured with the three cameras and the reference pattern of Fujifilm, and the third row shows the results of Canon. The left column is the results of wavelet-based method, and the right column is our method

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