INTERNATIONAL JOURNAL OF SCIENTIFIC PROGRESS AND RESEARCH (IJSPR) ISSN: 2349-4689
Issue 139, Volume 47, Number 02, May 2018

Source Camera Identification with the Help of Effective Sensor Pattern Noise Extraction By Digital Filtering Methods

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Abstract-The paper describes a different filtering method of noise removal which present in digital images. The method inputs an image which is taken by an unknown camera. The method proposed here makes use of image to identify the source camera by the help of unique fingerprint which will present in every camera because of the nonlinearity in pixel size & this will produce the unique noise pattern which is known as sensor pattern noise. In this paper we are using different filter methods which are used to improve the sensor pattern noise extraction which is the powerful tool forimage forensic.

Keywords-SPN, Noise filtering methods , bilinear filter, sigma filter,BM3D,Gaussian filter

I. INTRODUCTION

Digital forensics is a branch of forensic science to form a circle about therecovery &investigation of material found in digital devices. Digital forensic having three major parts..

Digital forensic

⇩

Computer forensic

Network forensic

Multimedia forensic

This paper covers a detailed description of image forensic which is the part of multimedia forensic.

Multimedia forensic

⇩

Image

Audio

Video

In forensic investigation digital images are not easily acceptable because it is difficult to establish their candor.

- Which camera captures the image?
- Is this a natural image or a computer graphics rendering?

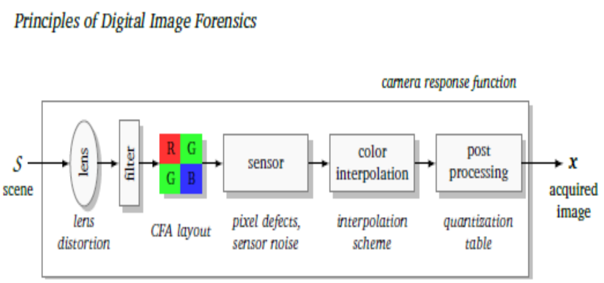
To avoid this problem we use forgery identification. This performed by source camera identification by device linking &fingerprint matching.

SPN (Sensor pattern noise) is define as any noise component that cannot be eliminated by averaging. Due to manufacturing imperfection & the difference in silicon wafer, the output of the pixel on the sensor may vary from each other even if they are exposed to the same illumination. Therefore a kind of pattern noise is introduced which is known as Photo Response Non Uniformality.

PRNU is an elemental property of all imagine sensor due to remote variation among every single pixels in their ability to convert photons to electrons. Consequently every sensor produce some amount of noise like pattern onto every image it takes & this pattern play a role of sensor fingerprint.

Image acquisition

Step1.	Camera
Step2	Light project
Step3	Amplification & quantization of energy
Step4	Signal adjusting
Step5	Colors Interpolation &demosaiking
Step6	Color & gamma correction Sharpening
Step7	Storing



This paper covers a detailed description of four de-noising filters and their use in image noise removal and SPN extraction.

II. IMAGE NOISE MODEL

In general the image noise model is defined as:

$$y = x + \eta , \qquad (3.1)$$

where x is original un-corrupted image, η is noise term and y is observed noisy image. For images corrupted with Gaussian noise; the term η follows Gaussian distribution.

III. FEW DE-NOISING FILTERS

Various de-noising filters have been developed so far. Few of the Gaussian noise removal filters are described here.

3.1 The Gaussian Filter

In signal processing, a Gaussian filter (GFlt) is a filter whose impulse response is a Gaussian function. The GFlts have the properties of having no overshoot to a stage work input while limiting the ascent and fall time. This conduct is firmly associated with the way that the GFlt has the base conceivable gathering delay. It is viewed as the perfect time space filter, similarly as the since is the perfect recurrence space filter [17] These properties are critical in territories, for example, oscilloscopes [18] and computerized media transmission systems [19].

Scientifically, a GFlt adjusts the information motion by convolution with a Gaussian function; this change is otherwise called the Weierstrass change.

3.2 The Wavelet Based De-noising Filter

This filter was initially proposed in [21], and it works as takes after. The fourth-level wavelet disintegration of the image with the 8-tap Daubechies quadrature reflects filter is first ascertained. Let the wavelet coefficients in the vertical, even, and corner to corner sub-bands be separately indicated by h(i,j), v(i,j), d(i,j), (i,j) ∈ T , where T is the record set of the wavelet coefficients that relies upon the disintegration level. The de-noised wavelet coefficients are gotten utilizing the Wiener filter:

$$h_{\omega}(i,j) := h\ (i,j)\frac{\hat{\sigma}^2(i,j)}{\hat{\sigma}^2(i,j)+\sigma_0{}^2} \qquad (3.2)$$

What's more, comparably for v(i, j) and d(i, j). $\sigma_0{}^2(i,j)$ is the change (variance) of the noise that is thought to be a white Gaussian process, furthermore, $\sigma^{\ 2}(i,j)$ speaks to the assessed nearby fluctuation of the wavelet coefficients of the "first" noise free image—these coefficients are demonstrated as locally stationary iid factors with zero mean. The most extreme aposteriori (MAP) estimation is utilized to acquire the nearby difference:

$$\hat{\sigma}_q{}^2(i,j) = \max(0, \frac{1}{q^2}\sum_{(x,y)\in B_a} h^2(x,z) - \sigma_0{}^2) \quad (3.3)$$

Where q×q is the measure of the window B_q around (i,j); it was proposed to set q ∈ {3, 5, 7, 9}. The base of the four differences is utilized as a part of (3.3), i.e.

$$\hat{\sigma}^{\ 2}(i,j) = \min(\hat{\sigma}_3{}^2(i,j), \hat{\sigma}_5{}^2(i,j), \hat{\sigma}_7{}^2(i,j), \hat{\sigma}_9{}^2(i,j))$$
(3.4)

The de-noised image is then gotten by applying the backwards wavelet change on the de-noised coefficients. It was appeared that the decision of $\sigma_0{}^2(i,j)$ has little effect on the execution of the filter in PRNU extraction. The creators, all through their different forms of this work, recommended setting σ_0 in the vicinity of 2 and 5.

3.3 The Bilateral Filter

A bilateral filter is a type of non-linear filter , having a property of edge-conservation, noise-reduction, smoothing filter for images. It changes the intensity of each pixel with a weighted average intensity value from near-by pixels. This weight can depend on Gaussian distribution.

Weight of pixels depends onsome very important parameter among which most prominent is their Euclidean distance but also taken consideration it depends on their the radiometric difference (e.g., range difference ,color intensity, depth , etc.). This conserves the sharp edges.

3.4 The BM3D Filter

Collaborative filtering is the name of the BM3D grouping and filtering strategy. It is acknowledged in four stages: 1) finding the image patches like a given image fix and gathering them in a 3D piece 2) 3D straight change of the 3D square; 3) shrinkage of the change range coefficients; 4) backwards 3D change. This 3D sifts along these lines filters through at the same time each of the 2D image fixes in the 3D square.

By constricting the commotion, collective sifting uncovers even the finest points of interest shared by the grouped patches. The separated patches are then come back to their unique positions. Since these patches cover, many appraisals are acquired which should be joined for every pixel. Total is a specific averaging method used to exploit this excess.

The primary communitarian sifting step is quite enhanced by a moment step utilizing Wiener separating. This second step mirrors the initial step, with two contrasts. The primary distinction is that it thinks about the separated fixes rather than the first fixes. The second distinction is that the new 3D gathering (worked with the natural image tests, yet utilizing the fix separations of the sifted image) is handled by Wiener sifting rather than a minor limit. The last total stride is indistinguishable to those of the initial step.

The BM3D strategy enhanced the NL-means [20] technique which de-noises mutually comparable patches, yet just by playing out a fix normal, which adds up to a 1D filter in

the 3D square. The 3D filter in BM3D is performed on the three measurements all the while.

The BM3D algorithm detailed here straightforwardly originates from the first article [21]. It is by and large considered to accomplish the best execution limits in color image de-noising. By and by, the creators have indicated out us later and advanced forms. Like for NL-implies, there is a variation with shape-versatile patches [22]. In this calculation designated BM3D-SAPCA, the sparsely of image portrayal is enhanced in two angles. To begin with, it utilizes image patches (neighborhoods) which can have information versatile shape. Second, the PCA bases are acquired by Eigen value corrosion of exact second-minute frameworks that are evaluated from a gathering of comparative versatile shape neighborhoods. This technique enhances BM3D particularly in saving image points of interest and presenting not very many ancient rarities. The anisotropic shape-versatile patches are gotten utilizing the 8-directional LPAICI methods [25]. In the extremely late improvements of BM3D [23, 24], it is summed up to end up noticeably a non specific image reclamation apparatus, including de-blurring.

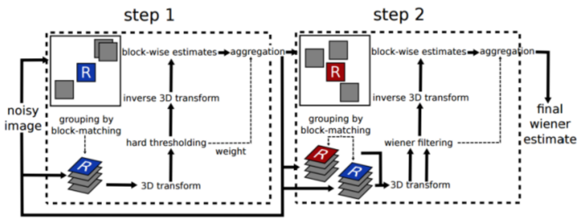


Fig 3.1: steps of BM3D algorithm [24].

3.5 The Sigma Filter

This is a non-linear variant of the linear averaging filter aiming to suppress noise without blurring the image too much.

"This filter will smoothes the image noise. Consequently, image edges are preserved, and subtle details and thin lines such as roads are maintained."

The filter became popular because it improves noisy images and flattens local differences with minimal loss of sharpness.

It replaces any pixel value by the majority of some, but not all pixels of its rectangular territory.

The idea is to exclude the outsiders which differ too much from the center and to restrict constitutional majority to a subset of sufficiently conformed neighbors.

Here is the pseudo-code for gray value images:

1. Take the pixel's gray value and add the gray values of those of its eight neighbors,

Which differ less than sigma?

2. Divide the sum by the no of the majority neighbors, get the integer value by round off the value

3. Write it to the output image at the same x,y position.

IV. DE-NOISING PERFORMANCE

4.1 Image Set

In this sub-section, we aim to compare the de-noising performance of different de-noising algorithms. The peak signal to noise ratio (PSNR) is used to evaluate the performance of different filters and higher PSNR value represents better de-nosing performances. It is worth mentioning that the standard deviation (SD) used in Gaussian, Bilateral, Sigma and BM3D filters is taken in the range [5,25]. Figure 3.3 shows PSNR values of four de-noising filters for different σ (SD).

Fig 3.2: Test images used in this work.

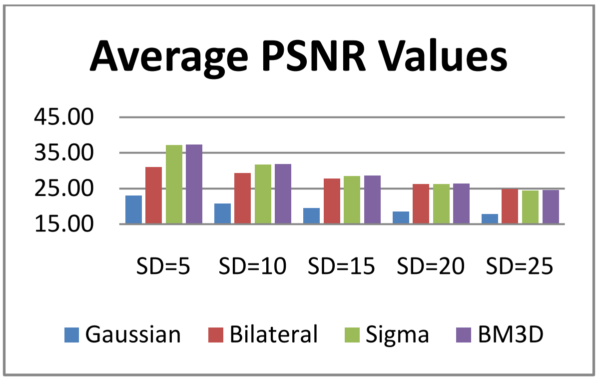


Fig 3.3: average PSNR values for different SD.

Since PRNU noise is quiet subtle, we only show the result with small σ. Experimental results illustrate the BM3D has highest PSNR values, followed sequentially by Sigma filter, thus can extract better PRNU noise than previous filters. We can conclude that BM3D is very sophisticated for white Gaussian noise (WGN) when the noise level is comparatively low. However for large amount of noise the Bilateral filter work better than other methods.

V. SPN EXTRACTION PERFORMANCES

5.1 Image Set

For conducting this experiment we have taken 750 images from five different cameras (150 each) of the Dresden image database [6]. Based on the detection statistics shown in the equation (2.7) we have checked performance of these SPN extraction de-noising filters. We have found correlation between the camera fingerprint and the SPN extracted from test image. If the correlation value is greater than 0.01 then we have concluded that the image is taken from that camera. The following table shows average true positive rate for threshold values 0.01;

Table 1, True Positive Rate for Threshold 0.01

Gaussian Filter	BM3D Filter	Sigma Filter	Bilateral Filter
41.33	44.00	49.33	0.53

So from table 1 we have concluded that Sigma filter performs far better than other methods. Thus under the given threshold it is the best method for SPN extraction.

At last the overall conclusion is:

1. For small amount of noise, Sigma and BM3D filters are working well.
2. For large amount of noise, bilateral filter is working well.
3. For SPN extraction Sigma filter is working far better than other filters and bilateral filter performs the worst.
4. So the conclusion is "".

VI. CONCLUSION

This chapter provided an analysis of de-noising filters for noise removal and SPN extraction. Initially in this chapter we have explained about various widely used Gaussian noise removal de-noising filters after that the filters are evaluated for noise removal as well as for SPN extraction. For de-noising examination experimental results illustrate the BM3D has highest PSNR values, followed sequentially by Sigma filter, thus can extract better PRNU noise than previous filters. We can conclude that BM3D is very sophisticated for white Gaussian noise (WGN) when the noise level is comparatively low. However for large amount of noise the Bilateral filter work better than other methods. For SPN extraction we have observed that Sigma filter performs far better than other methods. Thus under the given threshold it is the best method for SPN extraction.

Conclusion and Future Work

In this work we have shown perform of de-noising filers for SPN extraction. We basically aimed at establishing a relation in between the de-noising performance and SPN extraction performance of a de-noising filer. Initially this work provided a brief review of the digital image forensics field after that it gives a detailed description of the various methods developed for SPN extraction, SPN enhancement etc. At last this work shows an experimental analysis of the de-noising filters for noise removal and SPN extraction.

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