An Improved Sensor Pattern Noise Estimation Method Based on Edge Guided Weighted Averaging

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Abstract. Sensor Pattern Noise (SPN) has proven to be an effective fingerprint for source camera identification. However, its estimation accuracy is still greatly affected by image contents. In this work, considering the confidence difference in varying image regions, an image edge guided weighted averaging scheme for robust SPN estimation is proposed. Firstly, the edge and non-edge regions are estimated by a Laplacian operator-based detector, based on which different weights are assigned to. Then, the improved SPN estimation is obtained by weighted averaging of image residuals. Finally, an edge guided weighted normalized cross-correlation measurement is proposed as similarity metric in source camera identification (SCI) applications. The effectiveness of the proposed method is verified by SCI experiments conducted on six models from the Dresden data set. Comparison results on different denoising algorithms and varying patch sizes reveal that performance improvement is more prominent for small image patches, which is demanding in real forensic applications.

Keywords: Sensor pattern noise · Edge detection · Weighted averaging · Source camera identification

1 Introduction

Digital images play an increasingly indispensable role in human life. It is also an important information carrier that can be used to testify incidents and provide legally acceptable evidence for courtroom purposes. However, the credibility of images is reduced when they are maliciously tampered, which is undoubtedly a loss. To this context, the development of digital image forensics technology [1–3], such as integrity verification, source device linking, authentication and source camera identification (SCI), has drawn more attention in the past decades.

Sensor pattern noise (SPN) has long been an effective method in SCI problems that it is a unique fingerprint to identify a specific device of the same brand and camera model [4]. After one have accumulated certain number of images (blue-sky images with large smooth areas are preferable [5]) from the image sensor, a set of residual images are calculated by subtracting the denoised version from the original images. Then, different strategies are adopted to estimate SPN by aggregating the residuals. Many research works [6–15] have been developed based on SPN method, which can be roughly divided into three categories.

Employing better image denoising algorithms contributes to more accurate SPN estimation. The wavelet domain adaptive denoising filter [16] first adopted by Lukas et al. [6] is a common choice for image denoiser in early years [6, 7]. As spatial domain image denoising methods are less influenced by artifacts, Kang et al. developed a series of SPN methods [8–10]. As a representative work, Zhang et al. proposed a block weighted averaging module [11], which based the block variance of all extracted residuals, further suppress the effects of scene content. In our previous attempt [12], the enhanced restoration capability of Multi-Scale Expected Patch Log Likelihood (MSEPLL) has been verified, especially for small patch sizes. Cortiana et al. [13] conducted comprehensive comparison of different denoising filters and found that the BM3D denoising algorithm [17] demonstrates the best performance in SCI applications. How to obtain better residual images less influenced by image contents is an important direction in SPN estimation.

The second group of works focus on **residual image or SPN enhancement.** The zero-mean(ZM) and Wiener filtering in Fourier domain(WF) techniques proposed by Chen et al. [5] are widely adopted in SCI fields [9–11]. Six models were proposed to suppress the influence of scene content in [7] while a spectrum equalization algorithm was proposed in [14] for SPN enhancement.

Residual aggregation strategy that works on how to fuse all information from multiple images also plays an important role in SPN estimation. Besides direct averaging in [4] and the maximum likelihood estimation method in [5], the reciprocal of the variance of the entire residual is adopted as weights in [15] by Lawgaly et al.

Considering the fact that different image contents contributes varyingly to SPN estimation, an improved SPN estimation method is proposed in this work. Firstly, a Laplacian operator-based detector is adopted to distinguish edge and non-edge regions. Then, by weighting edge and non-edge regions of the residual, effective sensor pattern noise estimation is performed. In this way, the estimated SPN is less influenced by image contents while the problem of effective residual aggregation is addressed simultaneously. The effectiveness of the proposed method has been verified by three comparative tests, and the experimental results show that identification accuracy of most camera devices has been improved.

The remainder of this paper is organized as follows. Section 2 introduces the relevant work of this paper and Laplacian operator-based edge detectors [18]. The proposed SPN estimation method and similarity measure is presented in Sect. 3 in detail. Section 4 discusses experimental results, while Sect. 5 concludes the paper.

2 Related Works

2.1 The Influence of Edge Region

Generally, multiple natural images containing different scene details are adopted in SPN estimation, while the acquisition of blue-sky images is impossible in real forensic applications. This will greatly degrade the accuracy of SPN estimation as shown in Fig. 1. Due to the imperfectness of current image denoising algorithms, there are plenty image content related structures in residual images (see Fig. 1(c)), as compared to the idea SPN shown in Fig. 1(a). It is easy to get the conclusion that the obtained residual image is highly correlated to the edge region (Shown in Fig. 1(d)) of the original image. This is in consistent with the fact that smooth region is beneficial to the extraction of SPN, while the texture/edge region interferes with the estimation of SPN [7].

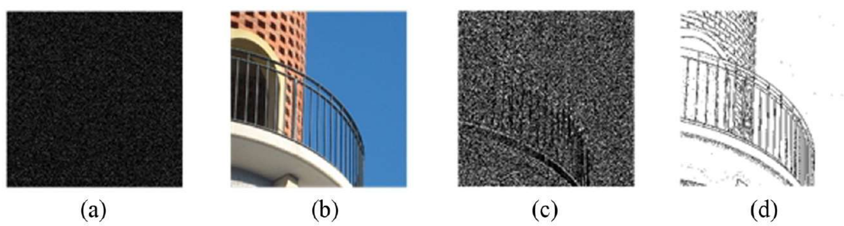


Fig. 1. The influence of edge region in SPN estimation. (a) The *SPN* estimated by blue-sky images. (b) An example of natural image. (c) Residual image extracted by GBWA [11]. (d) Edge image obtained by LOE [18].

There have been plenty works that tried to utilize this phenomenon to improve the SPN estimation accuracy. For example, the variance of image intensity is adopted as the texture complexity indicator [19], that only pixels in smooth region are utilized for further processing. In [20], Chan et al. studied the effect of image intensity as well as image texture features, based on which a nonlinear regression model is utilized for confidence map prediction, so that a pixel-wise weighting function could be obtained to penalize texture/edge pixels. In [21], a reliability map is obtained by inverted edge power, while a Gaussian filter is performed as well to make sure surrounding non-edge region are also assigned a lower weight.

In this work, we also adopt the same philosophy to unequaly weight edge, texture and smooth regions for SPN estimation. We will reply on a robust edge detector [18] for edge/non-edge region distinction. Meanwhile, we will show that the simple yet effective weighting strategy is a universal technique that benefits more accurate SPN estimation that it could be used in conjunction with several state-of-the-art image denoising algorithms.

2.2 The Laplacian Operator-Based Edge Detection Algorithm

In this section, we briefly introduce the Laplacian operator-based edge detectors [18], as we rely on this method for reliable edge/non-edge region distinguish.

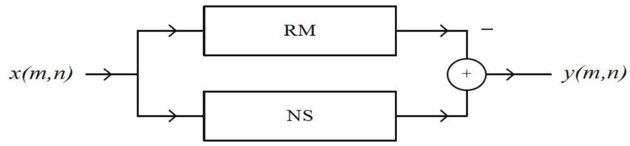


Fig. 2. The Laplacian operator-based edge detection model.

Based on the most popular Laplacian operator in edge detection, Xin Wang reformulated the Laplacian operator-based edge detection model (EDM) as shown in Fig. 2, where $x(m,n)$ and $y(m,n)$ represent the input and output images, respectively. The noise smoother (NS) is used to obtain edge information while smoothing noise and the round mean (RM) part is used to compute the local mean. Then, by a subtraction operation between the outputs of the two filters, the local high-frequency components of an image are obtained.

Considering the incorporation local non-linearity will benefit edge detection, the multistage median filter (MMF) is adopted as the noise smoother in this work. Imposing a Laplace distribution hypothesis of the output signal of the edge detection operator, the optimal MAP threshold T_0 is

$$T_0 = \frac{\sqrt{2}}{\sigma_{s1}} \sigma_{w1}^2. \tag{1}$$

where σ_{w1} and σ_{s1} are the standard deviation of noise and signal, respectively. The finally detected edge map E is obtained by

$$E(m,n) = \begin{cases} y(m,n) - \mathrm{sgn}[y(m,n)]T_0, & |y(m,n)| > T_0 \\ 0, & |y(m,n)| \leq T_0 \end{cases} \tag{2}$$

Readers may refer to [18] for more details in estimation of specific parameters.

3 The Proposed Edge Guided Weighted Averaging Method

In this section, we will first present the proposed edge guided weighted averaging method for SPN estimation. Then the framework of source camera identification and performance evaluation protocol is discussed.

3.1 SPN Estimation Based on Edge Guided Weighting

In order to reduce the influence of image contents as well as perform effective aggression from multiple residual images that corresponds to the same position in the same sensor, an image edge guided weighted averaging method is proposed.

As illustrated by the diagram in Fig. 3. that for each image, edge map E and residual images R are calculated simultaneously. Guided by the principle that non-edge region are more reliable thus higher weights should be assigned to, and edge region should be assigned with smaller weights. Considering the robustness of the LOE edge detector, a simple strategy is adopted that all pixels in edge region are equally weighted by a reduction parameter α without further distinguish in the edge intensity. Finally, the SPN is obtained by weighted average of residual images with respect to the weights. From the visual inspection of the obtained SPN, we see that it is less influenced by the image contents and looks more "white" as expected.

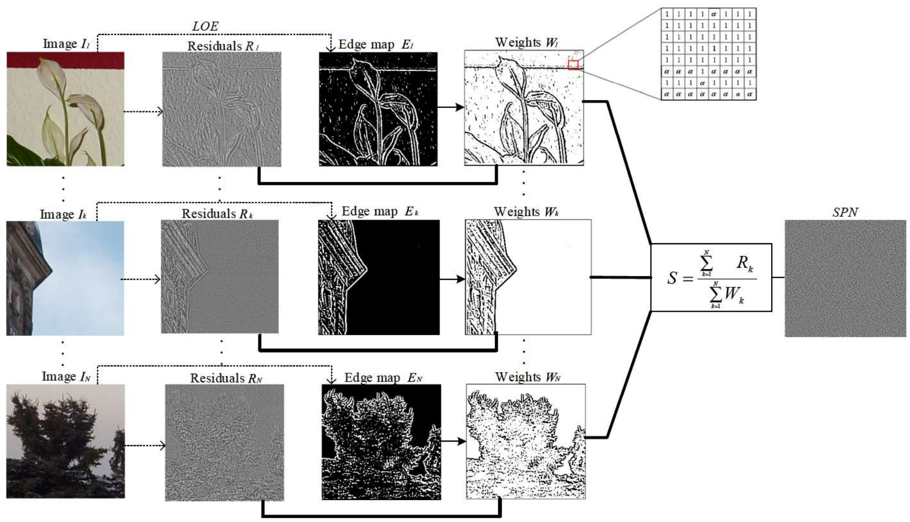


Fig. 3. The diagram of the proposed edge guided weighted averaging method for SPN Estimation.

To sum up, the proposed SPN estimation method is consisted of three steps as follows:

Step1. Obtain the residual image. Residuals image R is to subtract the denoised version from the original image I:

$$R = I - F(I), \tag{3}$$

where $F(\bullet)$ represents the denoising algorithm, We set the standard deviation of noise $\sigma_0 = 3$ when denoising following [5].
Step2. Obtain the weighting map. Utilizing *LOE* to obtain the edge region of image. In the weighting map W, the value of the edge region is set to α while non-edge is 1.
Step3. Obtain the camera SPN estimation and enhancement. Given a set of N images from the same camera instance, the estimated SPN is obtained by weighting average:

$$S = \frac{\sum_{k=1}^{N} W_k R_k}{\sum_{k=1}^{N} W_k}. \tag{4}$$

It is worth mentioning that the proposed edge guided weighted averaging method is a general SPN aggregation method that imposes no restriction on image denoising nor SPN enhancement algorithms. It could be adopted in conjunction with state-of-the-art SPN estimation or enhancement methods to further improve the estimation accuracy.

3.2 Source Camera Identification

In forensic applications, once the SPN of candidate imaging sensors have been estimated by the proposed edge guided weighted averaging method, source camera identification could be performed. To determine whether the image t under investigation was taken from a specific camera, one needs to calculate the similarity between the fingerprint of t (usually replaced by noise residue image when there is only one image at hand) and the SPN of the candidate camera. Among various similarity measurement, including Peak to Correlation Energy (PCE), cross-correlation, etc., normalized cross-correlation (NCC) is widely adopted due to its simplicity and stability.

As there is only one test image at hand in the testing phase, the influence of image content due to imperfection of denoising filters is more severe as compared with the case in SPN estimation where more images (usually 25/50) are available for aggregation. Based on previous discussion in assigning unequal weights to edge/non-edge regions, an edge guided weighted normalized cross-correlation (EWNCC), defined as

$$\rho_c = corr(W_t R_t, S_c) = \frac{(W_t R_t \bullet S_c)}{\|W_t R_t\| \bullet \|S_c\|}, \quad c = 1, 2, \ldots C \tag{5}$$

is proposed as the similarity measurement between noise residual R_t and the SPN of candidate camera S_c, W_t is the weighting map of the test image calculated according to the step2 in Sect. 3.1, and C is the total number of camera instances in consideration.

By assigning test image t to the camera that yields the largest NCC values among all C candidates, and then counting the number of correctly judgments (True) and wrong judgments (False) for each camera, the accuracy can be obtained as:

$$Accuracy_c = \frac{True}{True + False}. \tag{6}$$

4 Experiments and Discussion

4.1 Experimental Setup

To verify the effectiveness of the proposed algorithm, we conduct experiments on the public Dresden data set [22], following the experimental settings in [11]. All images from six cameras are selected for fairness in performance comparing, while details of the database are shown in Table 1. Depending on different settings, $N = 25$ or 50 randomly selected natural images are used for SPN estimation, while the remaining images are used for testing. Only central patches of sizes 64×64 and 128×128 are extracted for SPN estimation, as the source camera identification difficulty will greatly increase with the decline in patch size, which is demanding in real applications.

Table 1. Detail information of the experimental database.

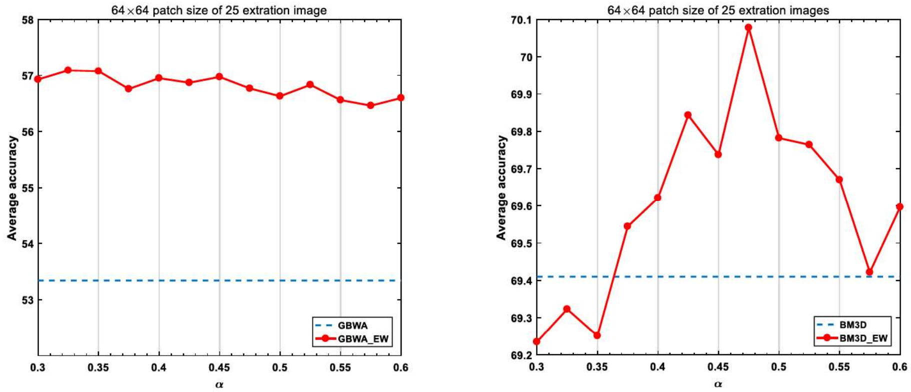
Camera No.	Image resolution	Device information	No. of images in Dresden
No.1	3264×2448	Canon_Ixus55_0	224
No.2	3872×2592	Nikon_D200_1	380
No.3	3648×2736	Olympus_mju_1050SW_4	202
No.4	3648×2736	Panasonic_DMC-FZ50_1	415
No.5	3072×2304	Samsung_L74wide_0	232
No.6	3456×2592	Sony_DSC-H50_0	284

Several methods are selected for performance comparison, including the basis method [4] which is a pioneering yet effective method in this field, the Model 3 in [7] that is a representative of SPN enhancement methods, the GBWA method [11] and BM3D method [13] that provide the state-of-the-art performance. We strictly follow all parameter settings and implementation details. No post-processing is adopted by BM3D while Fourier domain 3×3 Wiener filtering is applied to GBWA estimated SPN that retained artifact due to same in-camera processing algorithm could be reduced in some extent as claimed by the authors [11].

4.2 Determination of Weighting Parameter

As previously discussed in Sect. 3.1, α is an important parameter that determines the relative contribution of non-edge pixels, thus would directly affect the SPN estimation accuracy. Take the extreme case that $\alpha = 0$ for example, where all edge pixels are excluded in SPN estimation that some useful information would be lost. This should be avoided as edge pixels contain certain information, whereas being less reliable. However, α should not be set too large. As in the other extreme case $\alpha = 1$, edge pixels are considered equally contributing to the SPN estimation, which is obviously against our motivation. Generally speaking, the detection accuracy will first increase and then drop with the increase of α.

To determine the optimal value of α, we take GBWA [11] and BM3D [13] as baseline, the average detection performance of the proposed edge guided weighting



(a) (b)

Fig. 4. Average detection accuracy of proposed edge guided weighting under various settings of α for (a) GBWA and (b) BM3D methods.

(denoted as "*_EW") method are depicted with respect to different setting of α in Fig. 4 (patch size is set to be 64×64, while 50 images are used for SPN estimation).

We see that the edge guided weighted algorithm outperforms the baseline for both GBWA and BM3D in most α settings, with average identification accuracy improvement of 3.47% and 0.16%, respectively. The performance improvement with respect to α also obeys the first rise and then decline tendency as expected. In comprehensive consideration of performance and parameter robustness, we set $\alpha = 0.475$ uniformly for both SPN and EWNCC computation.

4.3 Source Camera Identification Performance Comparison

To verify the effectiveness of the proposed algorithm, we conduct comprehensive experiments and show results in Table 2 and Table 3 with 25 images for SPN estimation, for patch sizes of 64×64 and 128×128, respectively. In each table, bold figures indicate the highest identification accuracy among all six methods. To study the effectiveness of edge guided weighting algorithm with respect to baseline, methods demonstrating better performance are highlighted with gray background for both GBWA and BM3D groups.

Table 2. Accuracy Comparison for 64×64 patch size of 25 extracted images.

Method	No.1	No.2	No.3	No.4	No.5	No.6	Average (%)
Basic	42.71	50.42	40.11	45.64	38.65	73.75	48.55
Model3	27.64	61.41	40.11	57.69	31.40	72.20	48.41
GBWA	37.19	62.25	47.46	59.23	36.71	77.22	53.34
GBWA_EW	41.71	65.35	45.76	68.72	41.06	77.99	56.77
BM3D	52.7**6**	**82.82**	59.32	79.23	53.14	**89.19**	69.41
BM3D_EW	**53.27**	81.13	**61.02**	**82.05**	**54.59**	88.42	**70.08**

Table 3. Accuracy Comparison for 128 $\times$ 128 patch size of 25 extracted images.

Method	No.1	No.2	No.3	No.4	No.5	No.6	Average (%)
Basic	67.34	78.03	54.80	74.10	57.00	96.53	71.30
Model3	67.34	84.23	58.19	77.18	53.62	95.37	72.65
GBWA	71.36	87.04	**75.71**	81.03	63.29	95.75	79.03
GBWA_EW	74.37	91.27	67.80	87.44	72.46	94.21	81.26
BM3D	85.93	**98.31**	72.88	92.31	82.13	98.46	88.33
BM3D_EW	**87.44**	97.18	70.62	**93.59**	**85.02**	**98.46**	**88.72**

Generally speaking, BM3D based methods usually demonstrate best performance due to its powerful denoising ability. However, we find that the improvement of BM3D_EW over BM3D is very commendable. Furthermore, we can observe consistent performance improvement by the edge guided weighting for both GBWA and BM3D methods with average improvement of 2.83% and 0.53%, respectively.

We further investigate performance when increase the number of images to 50 for SPN estimation, while results are given in Table 4 and Table 5, while similar conclusions could be drawn. One may notice that GBWA algorithm achieved best performance in camera No.3 for patch size of 128 $\times$ 128. Further examination reveals that there are more flat and smooth regions in the images for Olympus in Dresden database. The block weighting mechanism in the GBWA [11] is an effective strategy that suits these types of images. This post-processing algorithm may be the reason for slightly better performance. However, averaged accuracy improvement over the GBWA method on the whole database is 3.43%, 2.23%, 3.87% and 1.53%, respectively. Meanwhile, we see that performance gain is more obvious for small patch size of 64 $\times$ 64, which is a very appealing property of the proposed method.

Table 4. Accuracy Comparison for 64 $\times$ 64 patch size of 50 extracted images.

Method	No.1	No.2	No.3	No.4	No.5	No.6	Average (%)
Basic	52.87	63.94	42.76	60.00	41.76	81.20	57.09
Model3	46.55	73.94	40.79	66.03	41.21	79.49	58.00
GBWA	55.75	72.12	47.37	70.41	45.60	87.18	63.07
GBWA_EW	62.07	75.15	50.66	75.89	51.10	86.75	66.94
BM3D	70.69	88.79	**61.18**	**87.67**	61.54	**97.01**	77.81
BM3D_EW	**70.69**	**88.79**	60.53	86.58	**67.03**	96.15	**78.29**

Table 5. Accuracy Comparison for 128 × 128 patch size of 50 extracted images.

Method	No.1	No.2	No.3	No.4	No.5	No.6	Average (%)
Basic	81.03	86.97	57.24	83.84	63.74	98.72	78.59
Model3	74.71	89.09	65.13	84.93	62.64	98.29	79.13
GBWA	85.63	93.94	**78.95**	87.40	68.68	98.72	85.55
GBWA_EW	85.06	95.15	76.32	91.51	75.27	99.15	87.08
BM3D	**94.25**	**99.09**	78.29	**95.62**	89.56	100.00	**92.80**
BM3D_EW	92.53	98.18	75.00	95.34	**92.86**	**100.00**	92.32

5 Conclusions

In this paper, a sensor pattern noise estimation scheme based on edge guided weighted averaging is proposed. By assigning different weights to the edge and non-edge pixels in the process of SPN estimation, contributions of smooth regions are emphasized thus estimation accuracy gain is obtained. Furthermore, an edge guided weighted normalized cross-correlation is proposed as similarity measure to handle less reliable edge pixels in test image. Finally, the robustness of parameter setting and effectiveness of the proposed method is verified through a series of experiments where consistent accuracy improvement is observed.

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