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INCREMENTAL UPDATE OF FEATURE EXTRACTOR FOR CAMERA IDENTIFICATION

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ABSTRACT

Sensor Pattern Noise (SPN) is an inherent fingerprint of imaging devices, which has been widely used in the tasks of digital camera identification, image classification and forgery detection. In our previous work, a feature extraction method based on PCA denoising concept was applied to extract a set of principal components from the original noise residual. However, this algorithm is inefficient when query cameras are continuously received. To solve this problem, we propose an extension based on Candid Covariance-free Incremental PCA (CCIPCA) and two modifications to incrementally update the feature extractor according to the received cameras. Experimental results show that the PCA and CCIPCA based features both outperform their original features on the ROC performance, and CCIPCA is more efficient on camera updating.

***Index Terms*—** Digital forensics, sensor pattern noise, camera identification, PCA denoising

1. INTRODUCTION

Digital camera identification is the process of linking digital images to the cameras that acquired them. Sensor pattern noise has been proved to be a reliable fingerprint of imaging device for digital camera identification. The deterministic component of SPN is the photo-response nonuniformity (PRNU) noise, which is primarily caused by the variable sensitivity of each sensor pixel to light. It is essentially slight variations in the intensity of individual pixels and an unique pattern deposited in every image taken by a sensor.

To determine whether a query image is taken by a suspect camera, three steps have to be taken. 1) The first step is the SPN extraction from the query image. Lukas *et al.* [1] first adopted a wavelet-based Wiener filter to extract SPN from digital image. After that several methods for SPN extraction or enhancement have been proposed. Dabov *et al.* [2] proposed a sparse 3D transform-domain collaborative filtering to extract SPN. Since PRNU is a kind of multiplicative noise, Chen *et al.* [3] proposed a Maximum Likelihood Estimation (MLE) method to estimate the corresponding multiplicative factor from the reference images. In [4], Li introduced a SPN enhancer to suppress the contamination caused by image content. A further investigation into SPN's location-dependent quality is reported by Li and Satta in [5]. In [6], Li *et al.* proposed a Colour-Decoupled PRNU extraction method to prevent the CFA interpolation noise from propagating into the physical components. In [7], Kang *et al.* introduced a context adaptive SPN predictor to suppress the impact of image content. 2) The second step is to estimate the reference SPN from the suspect camera, usually done by averaging multiple SPNs extracted from smooth images taken by that camera. 3) The final step is to detect whether the query SPN correlates to the suspect camera. Normalized cross-correlation is usually adopted as the detector statistics [1]. Later, Goljan *et al.* [8] introduced the Peak to Correlation Energy ratio (PCE) as a replacement for the normalized correlation detector. Another detection statistic CCN (correlation over circular correlation norm) is then proposed by Kang *et al.* [9].

There have been many efforts to improve the performance of digital camera identification. Some aimed at improving accuracy, others aimed at improving efficiency. In real applications, sensor fingerprint is usually extracted from large image blocks, since large image blocks contain more SPN information. However, the complexity of both SPN extraction and correlation detection are proportional to the number of pixels in noise residual. Hence the high dimensionality will make the process of camera identification time consuming. To solve this problem, Goljan *et al.* [10] proposed a fingerprint digest, which is formed by keeping only a small number of the largest fingerprint values and their positions. Later, Hu *et al.* [11] proposed a fast fingerprint digest search algorithm to further improve the identification efficiency. In [12], Bayram *et al.* proposed to represent sensor fingerprint in binary-quantized form, which speeds-up the correlation detection and also greatly reduce the size of fingerprint.

In a previous work, we employed the concept of PCA denoising [13] in digital camera identification. A feature extractor based on this concept was applied to extract a small number of components which contain most of the discriminative information of sensor fingerprint [14]. However, in real applications images taken by new cameras may be added to the database. In this case, it is infeasible to re-conduct PCA every time when a new data arrives. To address this problem, we propose an extension based on CCIPCA and two relevant modifications to incrementally update our feature extractor with the new images taken into account.

2. PROPOSED METHOD

2.1. PCA-based feature extraction

In SPN based camera identification, we usually extract noise residual from large image blocks to improve the identification accuracy, since large image blocks contain more SPN information. As a result, noise residual usually has a very high dimensionality (*e.g.* 1024×1024 pixels). However, the high-dimensional noise residual also tends to contain more redundancy and interfering components. For example, noise residual can be contaminated by color interpolation, JPEG compression, distortion introduced by denoising filter and other artifacts. Most of these artifacts are non-unique, redundant and less discriminant. Removing them will enhance the SPN signal in noise residual and improve the identification accuracy. Nevertheless, they are mixed with the real SPN signal in noise residual and it is very hard to separate them.

PCA [15] is a decorrelation method which has been widely used for dimensionality reduction and redundancy removal. In our case, we attempt to find a PCA transformed domain which can better separate the real SPN signal and these redundant features. By excluding these redundant features, we can extract a set of features which contain most of the discriminative information of SPN signal.

2.1.1. Optimization of training samples

However, SPN is a subtle signal which can be severely contaminated in noise residual by scene details. These scene details may significantly increase the number of irrelevant components. And these components will be more dominant than SPN signal. Without removing these strong contaminations from the training set, PCA is more likely to find a set of components that will represent these noisy components rather than the real SPN signal. To avoid this problem, two strategies are applied:

1) Sample selection. For training sample selection, we give the priority to the noise residual extracted from low-variation images. It is because such images are more close to the evenly lit scene and contain less scene details. Hence these images can better exhibit the changes caused by SPN in intensity between individual pixels. By choosing this kind of images for SPN extraction, it will capture the energy of true SPN in the training set and guide PCA to find a set of features that better represent the SPN signal rather than other noisy components.

2) SPN extraction. Several SPN extraction methods in the literature could be used here to further enhance the energy of SPN signal in training set. Note that this step would be more important when only natural images (with scene details) instead of low-variation images are available for training. Assume there are n images $\{I_i\}_{i=1}^{n}$ taken by c cameras $\{C_j\}_{j=1}^{c}$ in the database. We first extract noise residual from the $N\times N$-pixels blocks cropped from the centre of these full-sized images and reshape them into a set of column vectors $\{\boldsymbol{x}_i \in \mathbb{R}^{N^2\times 1}\}_{i=1}^{n}$ with zero mean. These n SPN vectors are then used as the training set.

2.1.2. PCA-based extractor and limitation

PCA is performed to seek a set of orthonormal vectors $\boldsymbol{v}_k$ and their associated eigenvalues λ_k. The vectors $\boldsymbol{v}_k$ and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix S

$$S = \frac{1}{n}\sum_{i=1}^{n}\boldsymbol{x}_i\boldsymbol{x}_i^T = AA^T \tag{1}$$

where $A{=}\frac{1}{\sqrt{n}}\left[\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n\right] \in \mathbb{R}^{N^2\times n}$. Notice that the dimensionality of SPN could be extremely high (*e.g.,* $N^2{=}1024^2$). Therefore, directly solving the eigenvalue decomposition problem of $S \in \mathbb{R}^{N^2\times N^2}$ incurs a prohibitive computational cost (with a complexity $O(N^6)$). To make PCA feasible for the high-dimensional SPN, we apply a fast method instead of computing these eigenvectors (when $n \ll N^2$). Assume $\boldsymbol{v}_k{}'$ is the unit eigenvector of $A^TA \in \mathbb{R}^{n\times n}$ with eigenvalue λ'_k. We could obtain $A^TA\boldsymbol{v}_k{}' = \lambda_k{}'\boldsymbol{v}_k{}'$. Multiplying both sides by A, we have $AA^T(A\boldsymbol{v}_k{}') = \lambda_k{}'(A\boldsymbol{v}_k{}')$, where $A\boldsymbol{v}_k{}'$ are the eigenvectors of $AA^T = S$ with eigenvalues $\lambda_k{}'$. Thus, instead of solving the eigenvalue decomposition of matrix S directly, we can calculate the eigenvectors $\boldsymbol{v}_k{}'$ via the smaller matrix $A^TA \in \mathbb{R}^{n\times n}$ and obtain the objective $\boldsymbol{v}_k$ by $\boldsymbol{v}_k = A\boldsymbol{v}_k{}'$. The obtained $\{\boldsymbol{v}_k\}_{k=1}^{n}$ are then normalized and sorted in the descending order according to their associated eigenvalues $\lambda_1 \geq \lambda_2 \geq ...\lambda_n$. Note that only when $n \ll N^2$, computing eigenvectors via this method (with a complexity $O(n^3)$) would be more effective than the traditional way.

The eigenvectors with the d largest eigenvalues are selected to form a feature extractor $M = [\boldsymbol{v}_1,...,\boldsymbol{v}_d] \in \mathbb{R}^{N^2\times d}$. We keep the top d eigenvectors corresponding to 99% of the variance as it could give us the best result. Based on this feature extractor M, we can obtain a new feature with much lower dimensionality by

$$\boldsymbol{y}_i = M^T\boldsymbol{x}_i, \quad i = 1,2,...,n. \tag{2}$$

where $\boldsymbol{y}_i \in \mathbb{R}^{d\times 1}$ is the compact version of the original vector $\boldsymbol{x}_i$. The experimental results in Section 3 show that this PCA-based feature could outperform its original feature according to the ROC analysis, which means the SPN signal has been further purified during this feature extraction.

However, there is a limitation of this PCA-based feature extraction algorithm. This system requires that all the training samples be available before feature extractor M is estimated. In real applications, new images taken by unknown cameras will be added to the database continuously. To ensure the accuracy, we have to repeat the entire training that includes these new images/cameras. This would incurs a costly re-computation and exorbitant memory-requirement burden. To overcome this limitation, an extension based on incremental learning scheme is employed in this work.

2.2. Incremental camera learning

Incremental learning method is usually adopted to add new samples to the original training set and update the PCA representation with less computational burden. CCIPCA was introduced in [16] to incrementally update the leading eigenvectors without estimating the covariance matrix. In this work, we propose a method based on CCIPCA to incrementally update feature extractor so as to accommodate the new received images/cameras. Assume we have already computed the initial feature extractor M from the original training set $\{\boldsymbol{x}_i\}_{i=1}^{n}$. We can generate $\hat{n}$ noise residual vectors $\{\hat{\boldsymbol{x}}_i\}_{i=1}^{\hat{n}}$ from the continuously received $\hat{c}$ cameras. To incrementally update the feature extractor according to these new cameras, we can use the following algorithm

Algorithm

Input:The initial feature extractor $M = [\boldsymbol{v}_1^0, \boldsymbol{v}_2^0, ..., \boldsymbol{v}_d^0]$, the new received SPN vectors $\{\hat{\boldsymbol{x}}_i \in \mathbb{R}^{N^2\times 1}\}_{i=1}^{\hat{n}}$ from $\hat{c}$ cameras;
Output: The new feature extractor $\hat{M} = [\boldsymbol{v}_1^{\hat{n}}, \boldsymbol{v}_2^{\hat{n}}, ..., \boldsymbol{v}_{\hat{d}}^{\hat{n}}]$ updated by $\hat{n}$ samples;
for $i = 1$ to $\hat{n}$ **do**
  step 1: $\boldsymbol{v}_{d+i}^0 = \frac{\hat{\boldsymbol{x}}_i}{\|\hat{\boldsymbol{x}}_i\|}$, $M{=}[\boldsymbol{v}_1^0, \boldsymbol{v}_2^0, ..., \boldsymbol{v}_{d+i}^0]{\in} \mathbb{R}^{N^2\times(d+i)}$;
  step 2: Initializing $\hat{\boldsymbol{x}}_i^1 = \hat{\boldsymbol{x}}_i$;
  for $k = 1$ to $d + i$ **do**
    step 3: $\boldsymbol{v}_k^i = \frac{n-l-1}{n}\boldsymbol{v}_k^{i-1} + \frac{l+1}{n}\hat{\boldsymbol{x}}_i^k\hat{\boldsymbol{x}}_i^{kT}\frac{\boldsymbol{v}_k^{i-1}}{\|\boldsymbol{v}_k^{i-1}\|}$;
    step 4: $\hat{\boldsymbol{x}}_i^{k+1} = \hat{\boldsymbol{x}}_i^k - \hat{\boldsymbol{x}}_i^{kT}\frac{\boldsymbol{v}_k^i}{\|\boldsymbol{v}_k^i\|}\frac{\boldsymbol{v}_k^i}{\|\boldsymbol{v}_k^i\|}$;
  end for
end for
step 5: After normalizing $[\boldsymbol{v}_1^{\hat{n}}, \boldsymbol{v}_2^{\hat{n}}, ..., \boldsymbol{v}_{d+i}^{\hat{n}}]$, selecting the first $\hat{d}$ leading eigenvectors to form a new feature extractor $\hat{M} = [\boldsymbol{v}_1^{\hat{n}}, \boldsymbol{v}_2^{\hat{n}}, ..., \boldsymbol{v}_{\hat{d}}^{\hat{n}}] \in \mathbb{R}^{N^2\times\hat{d}}$.

In this algorithm, $\boldsymbol{v}_k^i$ is the k-th eigenvector derived from the first received i sample vectors. $\hat{\boldsymbol{x}}_i^{k+1}$ means the residual of the sample $\hat{x}_i$ after subtracted by the projections in the first k eigenvectors $[\boldsymbol{v}_1^i, \boldsymbol{v}_2^i, ..., \boldsymbol{v}_k^i]$, and serves as the input data for the next iteration. By doing so, the residual left by the first k eigenvectors will be complemented in the computation of the higher order eigenvectors.

Compare to the algorithm in [16], the main contributions of our method are: 1) step 1 is introduced in this algorithm to support more eigenvector candidates for constructing the new feature extractor $\hat{M}$, which could improve the accuracy of extractor estimation for accommodating the new cameras. At the meantime, step 5 is proposed to keep the extractor low dimensionality by discarding the less important eigenvectors from all the candidates. 2) l is the weighting parameter. We run this algorithm with $l{=}-0.8$ to prevent from assigning too much weight to the new cameras and diluting the effect of old cameras. For each new arrived sample, the direction of every eigenvector will be adjusted once. To avoid too much adjustment for a signal camera, we use at maximum 5 samples from each newly received camera for updating.

3. EXPERIMENTS

3.1. Experimental setup

In this work, the noise residuals extracted by the methods in [3] (MLE) and [7] (Kang) are used as the original features. In order to testify the feasibility of the proposed method, the performance of these original features combined with and without the proposed scheme are compared. The experimental work are conducted over the Dresden Image Database [17]. A total of 1600 images from 8 cameras are involved in our experiments, each responsible for 200. These 8 cameras belong to 3 camera models, each camera model has 2∼3 different devices. These cameras are listed in Table 1. For each camera, we have 50 low-variation images for training and 150 images with scene details for testing. Hence there are 150×8 matching and 1050×8 mismatching pairs in total. In our experiments, MLE/Kang+8C-PCA indicates that all the noise residual are extracted by MLE/Kang method and the feature extractor is estimated by PCA which includes all the 8 cameras in the training process; 5C-PCA means only the 5 *initial*-cameras are involved in PCA training; and 5(3)C-CCIPCA denotes that the 5 *initial*-cameras are first applied by PCA to estimate the initial feature extractor and the rest 3 *added*-cameras are then sequentially added to update the initial feature extractor via our CCIPCA-based method.

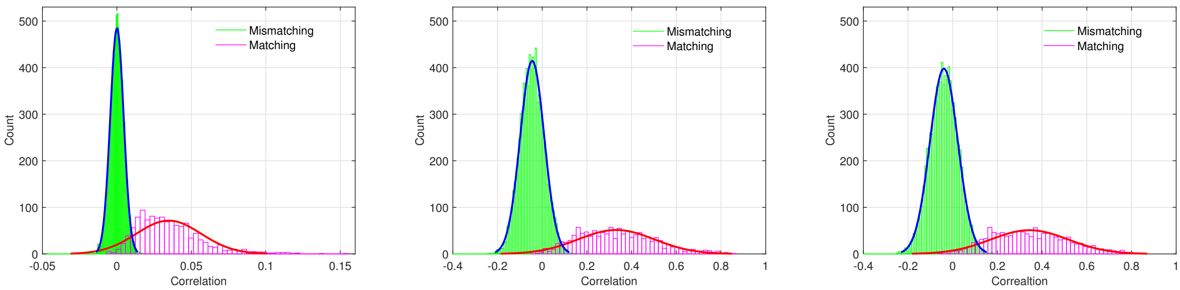
Table 1. Cameras from Dresden Database

Cameras	**Resolution**	**Satatus**
Canon_Ixus70_A	3072×2304	initial
Canon_Ixus70_B	3072×2304	initial
Nikon_CoolPixS710_A	4352×3264	initial
Samsung_L74wide_A	3072×2304	initial
Samsung_L74wide_B	3072×2304	initial
Canon_Ixus70_C	3072×2304	added
Nikon_CoolPixS710_B	4352×3264	added
Samsung_L74wide_C	3072×2304	added

3.2. Performance evaluation

Fig.1 shows the histograms of correlation values obtained from different methods. By comparing Fig. 1(a) with Fig. 1(b) and 1(c), we can see that after the feature extraction, the separation between intraclass and interclass is clearer and the overlapping area becomes smaller. It suggests that the features extracted by 8C-PCA or 5(3)C-CCIPCA are both superior than their original feature. But the performance of 8C-PCA is the upper bound of 5(3)C-CCIPCA. Such as in Fig. 1(c), we can see the tail of the mismatching distribution is wider than that in Fig. 1(b). This is mainly due to the approximation error between the principal components of PCA and those of CCIPCA. However, so far it still remains an *open question* and beyond the scope of this paper.

We use the overall Receiver Operating Characteristic (ROC) to compare the performances of different features, the experimental results are shown in Fig. 2 and Fig. 3. We



(a) Histograms for MLE method (b) Histograms for MLE + 8C-PCA (c) Histograms for MLE + 5(3)C-CCIPCA

Fig. 1. Histogram for the correlation values obtained from different methods, 256×256 pixels (Note the X-axis range).

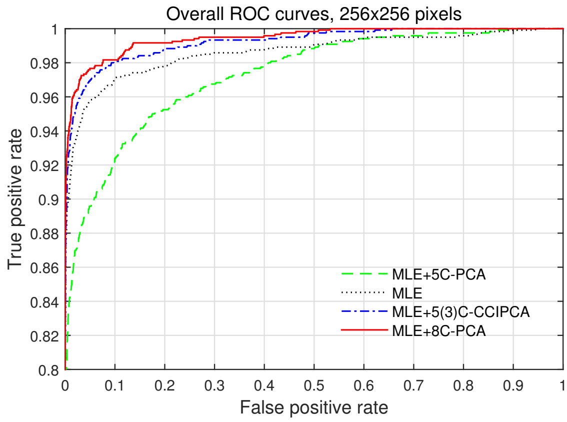


Fig. 2. ROC curves of different features based on MLE [3].

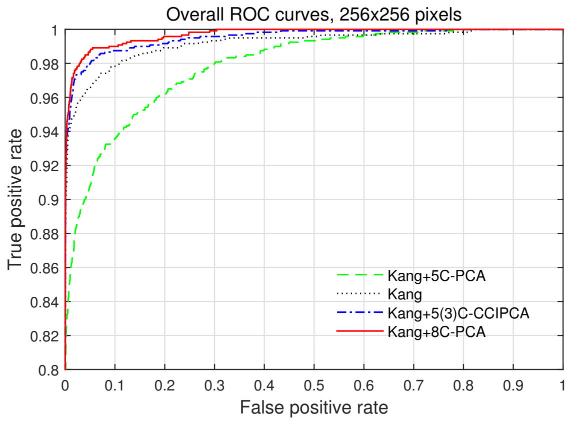


Fig. 3. ROC curves of different features based on Kang [9].

can see that: 1) The ROC performance of features extracted by 8C-PCA and 5(3)C-CCIPCA are both higher than that of the original features. It is because that the proposed feature extractor can further exclude the redundancy and interfering features from the noise residual obtained by the MLE or Kang method. 2) The ROC performance of 5C-PCA is the worst among the four methods. This is mainly because that this feature extractor is only estimated from the 5 *initial*-cameras, which is not accurate enough to represent the rest 3 *added*-cameras. Thus, there will be a large number of false positives from these 3 *added*-cameras. Repeating a training that includes these 3 *added*-cameras can regain the

Table 2. Computational time for updating a single camera to a training set with 10, 20 and 40 cameras, respectively.

	Training time (Seconds)		
	10+1 cameras	20+1 cameras	40+1 cameras
PCA	2.91	9.65	45.84
CCIPCA	0.85	0.86	0.86

accuracy, but it will incur costly re-computation especially when the number of overall cameras is huge. Therefore, our CCIPCA-based method is proposed to improve the efficiency. We can see from Table 2, the computational time can be significantly reduced by applying CCIPCA to update new cameras. 3) The ROC performance of 5(3)C-CCIPCA feature is very close to that of 8C-PCA. This is a good indication that the proposed incremental updating approach can not only significantly improve the updating efficiency, but also well preserve the identification accuracy.

4. CONCLUSION

In our previous work, a feature extraction algorithm based on PCA denoising was proposed to extract a feature set with much lower dimensionality from the original noise residual. In order to improve the reliability of this estimated feature extractor, in this work, two strategies are applied to optimize the training samples. However, this algorithm requires that all the cameras be available before feature extractor M is estimated. It would incur costly computation of re-conducting PCA whenever a new camera arrives. To solve this problem, a CCIPCA-based extension and two modifications are proposed to incrementally update the feature extractor so as to accommodate the newly received cameras. The experimental results show that PCA and CCIPCA based features both outperform their original features on the ROC performance. It suggests that the PCA-based feature extraction could serve as a post-processing scheme to purify the noise residual and further enhance the performance of other existing SPN extraction methods. Moreover, when facing the real-time online identification, our CCIPCA-based feature extraction method is an effective extension which can significantly reduce the computational complexity while preserving the identification accuracy.

5. REFERENCES

[1] J. Lukas, J. Fridrich, and M. Goljan, "Digital camera identification from sensor pattern noise," *IEEE Trans. Inf. Forensics Security*, vol. 1, no. 2, pp. 205–214, 2006.

[2] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3d transform-domain collaborative filtering," *IEEE Trans. Image Process.*, vol. 16, no. 8, pp. 2080–2095, 2007.

[3] M. Chen, J. Fridrich, M. Goljan, and J. Lukas, "Determining image origin and integrity using sensor noise," *IEEE Trans. Inf. Forensics Security*, vol. 3, no. 1, pp. 74–90, 2008.

[4] C.-T. Li, "Source camera identification using enhanced sensor pattern noise," *IEEE Trans. Inf. Forensics Security*, vol. 5, no. 2, pp. 280–287, 2010.

[5] C.-T. Li and R. Satta, "Empirical investigation into the correlation between vignetting effect and the quality of sensor pattern noise," *IET Computer Vision*, vol. 6, no. 6, pp. 560–566, 2012.

[6] C.-T. Li and Y. Li, "Color-decoupled photo response non-uniformity for digital image forensics," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 22, no. 2, pp. 260–271, 2012.

[7] X. Kang, J. Chen, K. Lin, and A. Peng, "A context-adaptive spn predictor for trustworthy source camera identification," *EURASIP Journal on Image and Video Processing*, vol. 2014, no. 1, pp. 1–11, 2014.

[8] M. Goljan, "Digital camera identification from images - estimating false acceptance probability," in *Proc. of International Workshop on Digital-forensics and Watermarking*, pp. 454–468. 2009.

[9] X. Kang, Y. Li, Z. Qu, and J. Huang, "Enhancing source camera identification performance with a camera reference phase sensor pattern noise," *IEEE Trans. Inf. Forensics Security*, vol. 7, no. 2, pp. 393–402, 2012.

[10] M. Goljan, J. Fridrich, and T. Filler, "Managing a large database of camera fingerprints," in *Proc. SPIE, Electronic Imaging, Media Forensics and Security XII*, San Jose, CA, USA, Jan. 17C21, 2010, vol. 7541, pp. 08 01–12.

[11] Y. Hu, C.-T. Li, and Z. Lai, "Fast source camera identification using matching signs between query and reference fingerprints," *Multimedia Tools and Applications*, pp. 1–24, 2014.

[12] S. Bayram, H. Sencar, and N. Memon, "Efficient sensor fingerprint matching through fingerprint binarization," *IEEE Trans. Inf. Forensics Security*, vol. 7, no. 4, pp. 1404–1413, 2012.

[13] D. Zhang, R. Lukac, X. Wu, and D. Zhang, "PCA-based spatially adaptive denoising of CFA images for single-sensor digital cameras," *IEEE Trans. Image Process.*, vol. 18, no. 4, pp. 797–812, 2009.

[14] R. Li, C.-T. Li, and Y. Guan, "A compact representation of sensor fingerprint for camera identification and fingerprint matching," in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, Brisbane, Australia, Apr. 19-24, 2015.

[15] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, 2nd ed. New York: Academic, 1991.

[16] J. Weng, Y. Zhang, and W.S. Hwang, "Candid covariance-free incremental principal component analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 8, pp. 1034–1040, 2003.

[17] T. Gloe and R. Böhme, "The dresden image database for benchmarking digital image forensics," *Journal of Digital Forensic Practice*, vol. 3, no. 2-4, pp. 150–159, 2010.