A COMPACT REPRESENTATION OF SENSOR FINGERPRINT FOR CAMERA IDENTIFICATION AND FINGERPRINT MATCHING

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ABSTRACT

Sensor Pattern Noise (SPN) has been proved as an effective fingerprint of imaging devices to link pictures to the cameras that acquired them. In practice, forensic investigators usually extract this camera fingerprint from large image block to improve the matching accuracy because large image blocks tend to contain more SPN information. As a result, camera fingerprints usually have a very high dimensionality. However, the high dimensionality of fingerprint will incur a costly computation in the matching phase, thus hindering many interesting applications which require an efficient real-time camera matching. To solve this problem, an effective feature extraction method based on PCA and LDA is proposed in this work to compress the dimensionality of camera fingerprint. Our experimental results show that the proposed feature extraction algorithm could greatly reduce the size of fingerprint and enhance the performance in term of Receiver Operating Characteristic (ROC) curve of several existing methods.

Index Terms— Digital forensics, Sensor pattern noise, Photo-response nonuniformity noise, PCA denoising

1. INTRODUCTION

Sensor pattern noise, produced by imaging sensors, has been proved to be an effective way for source camera identification. The photo-response nonuniformity noise is the deterministic component of SPN, which is primarily caused by the different sensitivity of individual sensor pixels to light. It is essentially the slight variations in the intensity of individual pixels and an unique pattern deposited in every image taken by a sensor.

Lukas *et al.* [1] first adopted a wavelet-based Wiener filter to extract the SPN from digital image. After that several works [2–11] have been done to improve the performance of SPN-based source camera identification. Many of them have achieved nearly perfect identification rate when SPNs are extracted from the image blocks with high resolution. However, the complexity of computing correlation for fingerprint matching is proportional to the dimensionality of SPN. Therefore, the SPN extracted from large image block, which has a high dimensionality, will incur an expensive computational cost in the matching phase especially when there is a sizable database involved. For example, in practice investigators may face the problems of looking for a particular fingerprint in a large database which contains a huge number of fingerprint matching. To address this issue, an intuitive idea is to reduce the dimensionality of SPN. In [12], Goljan *et al.* proposed a *fingerprint digest* as a possible solution. This fingerprint digest is primarily formed by only keeping a fixed number of the largest fingerprint values and their positions. In [13], Bayram *et al.* proposed to represent sensor fingerprint in binary-quantized form, which greatly reduce the size of fingerprint and speeds-up the correlation detection.

In this paper, we employ the concept of PCA denoising [14] in the SPN-based source camera identification. An effective feature extraction algorithm based on this concept is first applied to extract a small number of principal components that will better represent the SPN signal. LDA is then utilized to take the advantage of the observed label information of training samples (reference fingerprints) to further reduce the dimensionality and improve the matching accuracy.

2. PROPOSED METHOD

2.1. PCA-based Feature Extraction

In digital camera identification, noise residual is usually extracted from large image block to improve the identification accuracy, since the large image block contains more SPN information. As a result, noise residual usually has a very high dimensionality (e.g. 1024×1024 pixels). Nevertheless, the high-dimensional feature is more likely to introduce 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. However, they are mixed with the real SPN signal in noise residual and it is very hard to separate them.

PCA [15] is a well-known decorrelation method which has been widely used for dimensionality reduction or redundancy removal. In this work, 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 feature set which contain most of the discriminative information of the SPN signal.

2.1.1. Training sample selection

Assume there are n images $\{I_i\}_{i=1}^{n}$ taken by c cameras $\{C_j\}_{j=1}^{c}$ in a database, each camera has L_j images. We first extract noise residuals 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 $\{\boldsymbol{x}_i \in \mathbb{R}^{N^2\times 1}\}_{i=1}^{n}$. Several SPN extraction methods in the literature could be used here.

As mentioned in [5], image content would seriously contaminate the real SPN, and their magnitude is far greater than that of the real SPN. Without removing these strong contaminations from the training set, PCA is more likely to find a subspace that better represent these noisy components rather than the SPN signal. Therefore, for training sample selection, we give the priority to the noise residual extracted from low-variation images (*e.g.,* blue sky 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. Such a training sample selection 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.

2.1.2. PCA-based feature extractor

Let $\boldsymbol{\Psi} = \frac{1}{n}\sum_{i=1}^{n}\boldsymbol{x}_i$ be the mean of the training set. Each $\boldsymbol{x}_i$ differs from the mean $\boldsymbol{\Psi}$ by the vector $\boldsymbol{\Phi_i} = \boldsymbol{x}_i - \boldsymbol{\Psi}$. Then PCA is performed to seek a set of orthonormal vectors $\boldsymbol{u}_k$ and their associated eigenvalues λ_k. The vectors $\boldsymbol{u}_k$ and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix S

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

where A=$[\boldsymbol{\Phi_1}, \boldsymbol{\Phi_2}, \ldots, \boldsymbol{\Phi_n}]$. However as aforementioned, the dimensionality of fingerprint could extremely high (*e.g.,* $N\times N$=1024×1024). Thus directly solving the eigenvalue decomposition problem on the huge matrix $S \in \mathbb{R}^{N^2\times N^2}$ would 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 to compute these eigenvectors (when $n \ll N^2$). Assume $\boldsymbol{u}_k{}'$ are the unit eigenvectors of $A^TA \in \mathbb{R}^{n\times n}$ with eigenvalue λ_k'. We could obtain $A^TA\boldsymbol{u}_k{}' = \lambda_k{}'\boldsymbol{u}_k{}'$. Multiplying both sides by A, we have $AA^T(A\boldsymbol{u}_k{}') = \lambda_k{}'(A\boldsymbol{u}_k{}')$, where $A\boldsymbol{u}_k{}'$ are the eigenvectors of $AA^T = S$ with eigenvalues $\lambda_k{}'$. Thus, instead of finding the eigenvectors $\boldsymbol{u}_k$ of matrix S directly, we can calculate the eigenvectors $\boldsymbol{u}_k{}'$ of the smaller matrix $A^TA \in \mathbb{R}^{n\times n}$ and obtain the objective eigenvector $\boldsymbol{u}_k$ by $\boldsymbol{u}_k = A\boldsymbol{u}_k{}'$. The obtained $\{\boldsymbol{u}_k\}_{k=1}^{n}$ are then normalized to the unit vectors and sorted in the descending order according to their associated eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots\lambda_n$. Note that in practice the size of the training set tends to be much smaller than the dimensionality of SPN ($n \ll N^2$). Thus computing eigenvectors via this method (with a complexity $O(n^3)$) thus will be more effective than the traditional way.

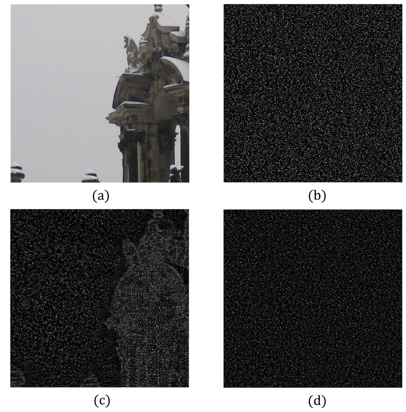


Fig. 1: (a) An image taken by Canon Ixus70. (b) Clean reference SPN of Canon Ixus70. (c) The noise residual extracted from (a) via the Winer filter [1]. (d) The reconstructed version of (c) via the proposed method. (Note the intensity of Fig. 1(b), (c) and (d) has been scaled to the interval [0,255] for visualization purpose.)

By excluding the eigenvectors with small eigenvalues while preserving the eigenvectors with large eigenvalues, we can obtain a small set of eigenvectors which contain most of the discriminative information of the SPN signal. In this work, the eigenvectors with the d largest eigenvalues are selected to construct the feature extractor $M_{pca} = [\boldsymbol{u}_1, ..., \boldsymbol{u}_d] \in \mathbb{R}^{N^2\times d}$. 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

$$\boldsymbol{y} = M_{pca}^T\boldsymbol{x} \tag{2}$$

where $\boldsymbol{y} \in \mathbb{R}^{d\times 1}$ is the compact version of the original vector $\boldsymbol{x}$. We call this new representation $\boldsymbol{y}$ as "PCA feature" in the rest of the paper.

According to the PCA feature $\boldsymbol{y}$ and the feature extractor M_{pca}, we can easily obtain a reconstructed SPN in the spatial domain via the inverse PCA transformation $\boldsymbol{x}' = M_{pca}\boldsymbol{y}$, where $\boldsymbol{x}'$ is an approximation of $\boldsymbol{x}$ (when $d<n$). By preserving only the principal eigenvectors and conducting the inverse PCA transformation, we find that the impact of image content can be effectively suppressed in the reconstructed version. As shown in Fig. 1(c), the image content in Fig. 1(a) propagate through the Wiener filter into the noise residual, but these scene details have been significantly suppressed after the SPN reconstruction Fig. 1(d). The reason for this phenomenon is that, the objective of our PCA-based feature extractor is to extract a set of features that will better represent the primary signal in the training set, thus the aforementioned training sample selection will guide it to extract features that represent the SPN signal rather than other contaminated

signals. Moreover, since the magnitude of image content is not similar with that of true SPN at all [5], our PCA-based feature extractor can easily distinguish and separate them.

To further prove this concept, we calculate the signal-to-noise ratio (SNR) between the signal of interest (SPN) and the contaminants in the noise residual (Fig. 1(c)) and reconstructed SPN (Fig. 1(d)), respectively. Since we have the clean SPN $\hat{\boldsymbol{x}}$ (Fig. 1(b)), the contaminations Ξ in the noise residual or reconstructed SPN can be approximately estimated by subtracting the clean SPN from the observed data. Thus SNR could be obtained as $10\log_{10}\frac{var(\hat{\boldsymbol{x}})}{var(\Xi)}$. The results show that the reconstructed SPN has a higher average SNR (6.2 dB) than the noise residual (-9.8 dB).

2.2. LDA-based Feature Extraction

Since the training set is labeled, LDA can use this information to further reduce the dimensionality. The purpose of LDA is to find a transformation matrix M_{lda} which can best separate different classes. This optimal matrix can be obtained by maximizing the ratio of the determinant of the between-class scatter matrix S_b to the determinant of the within-class scatter matrix S_w

$$M_{lda} = \arg\max_{J} \left| \frac{J^T S_b J}{J^T S_w J} \right| \tag{3}$$

The within-calss scatter matrix S_w is defined as $S_w = \sum_{j=1}^{c}\sum_{i=1}^{L_j}(\boldsymbol{y}_i - \boldsymbol{m}_j)(\boldsymbol{y}_i - \boldsymbol{m}_j)^T$, where $\boldsymbol{y}_i$ is the i^{th} sample of class j, $\boldsymbol{m}_j$ is the mean of class j, c is number of classes, L_j is the number of samples in class j. The between-class scatter matrix S_b is defined as $S_b = \sum_{j=1}^{c} L(\boldsymbol{m}_j - \boldsymbol{m})(\boldsymbol{m}_j - \boldsymbol{m})^T$ where $\boldsymbol{m}$ is the global mean of all samples. Having the matrix M_{lda}, a $(c-1)$ dimensional vector z can be obtained by

$$\boldsymbol{z} = M_{lda}^T \boldsymbol{y} = M_{lda}^T M_{pca}^T \boldsymbol{x} = T\boldsymbol{x} \tag{4}$$

where $\boldsymbol{z}$ can be seemed as another compact representation of the original noise residual $\boldsymbol{x}$, we call this new feature $\boldsymbol{z}$ as "LDA feature" in the rest of this paper. And T is the PCA+LDA-based feature extractor.

2.3. Reference Estimation and Detection Statistics

By performing the LDA-based feature extraction on the training set $\{\boldsymbol{x}_i\}_{i=1}^n$, we can obtain a set of LDA features $\{\boldsymbol{z}_i\}_{i=1}^n$. The reference feature $\boldsymbol{z}'_j$ for each camera C_j then can be estimated by averaging all the L_j features belong to that camera as $\boldsymbol{z}'_j = \sum_{i=1}^{L_j} \boldsymbol{z}_i / L_j$, $j = 1, 2, ..., c$.

The Normalized Cross-Correlation (NCC) is adopted as the detection statistics to measure the similarity between the query $\boldsymbol{z}$ and the camera reference $\boldsymbol{z}'$

$$corr(\boldsymbol{z}, \boldsymbol{z}') = \frac{(\boldsymbol{z} - \bar{\boldsymbol{z}})(\boldsymbol{z}' - \bar{\boldsymbol{z}}')}{\|\boldsymbol{z} - \bar{\boldsymbol{z}}\| \, \|\boldsymbol{z}' - \bar{\boldsymbol{z}}'\|} \tag{5}$$

where $\bar{\boldsymbol{z}}$ and $\bar{\boldsymbol{z}}'$ are the means of $\boldsymbol{z}$ and $\boldsymbol{z}'$, respectively. Notice that the complexity of computing correlation is proportional to the dimensionality of the features. Since the dimensionality of LDA feature $\boldsymbol{z} \in \mathbb{R}^{(c-1)\times 1}$ is much lower than that of the original noise residual $\boldsymbol{x} \in \mathbb{R}^{N^2 \times 1}$ ($c - 1 \ll N^2$), using the feature $\boldsymbol{z}$ as a compact representation of $\boldsymbol{x}$ in the matching phase could greatly reduce the computational complexity.

3. EXPERIMENTS

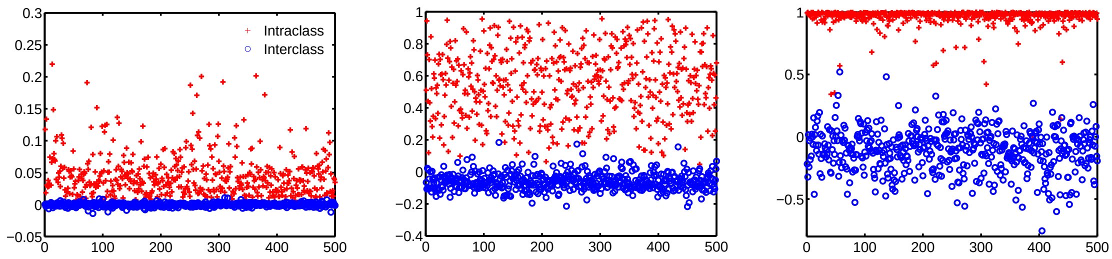
In this work, the noise residuals extracted by the methods in [1] (Lukas), [5] (Li's Model 3) and [9] (Kang) are used as the original features. In order to testify the feasibility of the proposed method, the performance of these original features combined with and without the proposed scheme are compared. Our experimental work are conducted over the Dresden Image database [16]. A total of 2000 images from 10 cameras are involved in the first experiment, each responsible for 200. These 10 camera devices belong to 4 camera models, each camera model has 2$\sim$3 different devices. For each camera, we have 50 low-variation images for training and 150 query images with scene details for testing. Thus there are 150×10 intraclass and 1350×10 interclass correlation values in total. We extract all the noise residuals from the luminance channel as the luminance channel contains information of all the three channels.

Fig.2 shows the distribution with respect to randomly selected 500 intraclass and 500 interclass correlation values according to different features, where "Original feature" indicates the noise residual extracted by Kang's algorithm. It can be seen that using the LDA feature can better separate the intraclass and interclass samples than the original feature or PCA feature. To further testify the accuracy, all the 150×10 intraclass and 1350×10 interclass samples are used to draw the overall ROC curves [9]. As shown in Fig. 3, the black, blue and red lines indicate the performance of the original features, PCA features and LDA features, respectively. It can be concluded from Table 2 and Fig. 3 that our PCA-based feature extraction could enhance the performance of the original SPN extraction method, and PCA+LDA-based feature extraction could further improve it. Based on Table 1, we can obtain the detection threshold for each features when they have the low False Positive Rate (FPR) (10^{-3}).

Table 1: The TPR of different features at the FPR of 10^{-3}

Methods	Original SPN	PCA	PCA+LDA
Lukas [1]	83.65%	95.55%	**99.21%**
Li's Model 3 [5]	85.97%	96.23%	**99.40%**
Kang [9]	93.20%	98.87%	**99.27%**

In practice, forensic investigators may face the problem that the query images are not taken by the existing cameras in the database. Therefore, we use 150×6 testing images taken by another 6 cameras from the Dresden database as query to further testify the performance of our proposed method. We calculate the NCC between these 150×6 query samples and the aforementioned 10 camera references. By comparing these $150 \times 6 \times 10$ interclass samples with the threshold obtained from Table 1, we can get the FPR of different features in Table 2. From Table 2 we can see that both PCA



(a) Original feature (b) PCA feature (c) LDA feature

Fig. 2: Distribution of the correlation values obtained based on different features, 512×512 pixels.

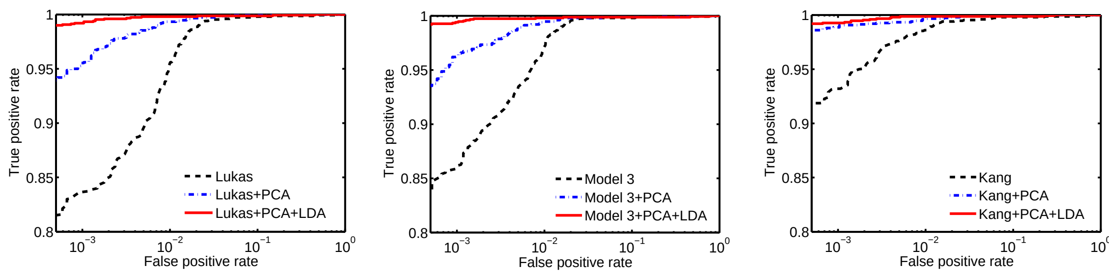


Fig. 3: The overall ROC comparisons among original features, PCA features and LDA features, 512×512 pixels.

Table 2: The FPR of different features

Methods	**Original SPN**	**PCA**	**PCA+LDA**
Lukas [1]	0.07%	0.03%	0.11%
Li's Model 3 [5]	0%	0%	0.04%
Kang [9]	0.02%	0%	0.05%

feature and LDA feature are able to make out that these testing samples are not taken by the aforementioned 10 camera, even though their fingerprints are not included in the training set.

Fig. 4 presents the time cost of different features for matching a fingerprint against a simulate database with 300 cameras, where "SPN extraction" indicates the time cost of extracting SPN from a query image via Kang's method, "Projection" represents the time cost of feature extraction via PCA and LDA, "Matching" is the time cost of matching a query fingerprint against 300 cameras and the overall time is evaluated by "Total". *Notice that the time cost of training is not counted in this figure as it could be performed at off-line.* All the experiments are conducted on the same PC with an Intel Core i5 3.20GHz processor and 16G RAM. It can be observed from Fig. 4 that although using PCA and LDA will incur an extra time cost in feature extraction, they dramatically reduce the time costs of matching process. Based on the overall time cost, we can conclude that the proposed method could greatly reduce the time cost of fingerprint matching with a large camera database. However, there is a potential limitation of LDA feature. Since the dimensionality of LDA feature is $c - 1$, the computational cost of matching process based on LDA feature might be also expensive when the number of camera in the database c is huge. But for this case, the dimensionality of PCA feature will still stay at a constant low level as it only depends on the dominance of the primary

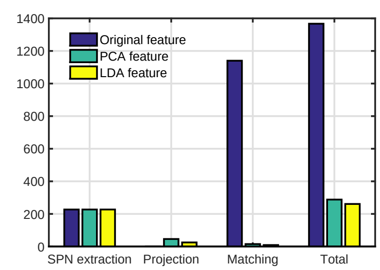


Fig. 4: Time cost of different features, 512×512 pixels.

signal in the training set.

4. CONCLUSION

In this work, we evaluate the concept of PCA denoising in source camera identification. A feature extraction algorithm based on this concept is proposed to extract a feature set with much lower dimensionality from the original noise residual. LDA is then adopted to take the advantage of the observed label information of the training data to better separate different classes and further reduce the dimensionality. By applying the proposed feature extractor on the noise residual, the SPN components could be well preserved while the dimensionality being effectively reduced. The experimental results show that the proposed feature extraction method could greatly improve the matching efficiency and further enhance the performance of several SPN extraction methods in the literature. However, this method is hard to address the problem that there are new cameras sequentially added into database. It is because that repeating an entire training that includes these new cameras would incur a costly re-computation. To solve this issue will be the focus of our future research.

5. REFERENCES

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