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A Hybrid approach for Camera-Model Detection

Shang Gao*

Information Center of Guangdong Power Grid Co., Ltd.
Gaoshang@gdxx.csg.cn

Abstract

In this paper, we propose a camera-model detection method based on a hybrid approach. Varying camera inside imaging processing will lead to varying artifacts. A few of artifacts can reflect camera model-specific. To comprehensive track camera model-specific footprint, we build a hybrid approach by combining two-step Markov feature based model and CFA feature based model. A 132-D feature set is designed to perform camera-model classification. Images from seven camera models in the Dresden Image Database are chosen as our experiment database. Experiment results show that in seven models detection, the average detection accuracy of our method is 99.83%. Even the feature dimension is decreased to 40 by feature selection; its detection accuracy can still reach to 99.58%, which is higher than that of previous Markov method [12].

Keywords: *Camera Model Detection, Two-step Transition Matrix, CFA Artifacts, Feature Selection*

1. Introduction

Recently, more and more people use digital camera images record their life and past. However, digital camera images can be easy changed, or faked, when they appear in court as evidence, they become controversial. Court needs credible proof of their source and authenticity. Although watermarking is mature [16-18], it can't be forced to plug in all digital devices. In this case, passive forensics is needed.

In passive forensics, source camera model identification is one of the most popular research directions; it tries to address the problem of image source verification. Generally speaking, the approaches can be achieved by finding out difference of hardware component or digital image processing (DIP) which usually vary from model to model. In recent years, some associated works have been published. For instance, reference fixed noise pattern method [1-3]; feature classification method, such as color features, wavelet statistics and image quality metrics [4]; radial distortion parameters [5]; CFA and interpolation features [6-9]; Markov matrix [12]; previous forensics features for source cell phones detection [10]; dust model for individual DSLR cameras discriminating [11], etc.

In this paper, a camera-model detection method is proposed. We present a hybrid forensics model to capture artifacts introduced by camera imaging processing. Experiment images are from 'Dresden Image Database'. Besides, feature selection method will be utilized to decrease feature dimensions. The results show even using low dimension features, our method can still performance excellent in detection. This paper is organized as follow: Section 2 describes the hybrid forensics model for detection. Section 3 and section 4 introduces the Markov features and the CFA features. The experiment results are given in section 5. Section 6 concludes this paper. And acknowledgement is in section 7.

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2. Hybrid Forensics Model for Detection

Nature image statistics classification approach is popular in camera model detection, and most statistics methods only use one forensics approach to model different camera images. Usually, one forensics approach only focuses on one factor caused by model-specific. But sometimes, camera models, which need to be distinguished, have similar or even same components or image processing algorithms. In this case, one forensics approach may not work perfectly. To overcome this shortage, we combine more than one forensics methods and build a hybrid forensics model for detection.

There are two kinds of forensics models for camera source detection. One is capturing different artifacts caused by whole camera imaging procedure, and the other is capturing different artifacts caused by a single camera inside component or an image processing algorithm. Among the first approaches, Markov matrix method performance good in classification. Previous work uses one-step Markov processing and four difference 2-D JPEG arrays along four directions [12]. Considering more hypothesis possibility will be more favorable for classification issue, it can be expected that the detection accuracy can also increase by more hypothesis conditions. In this paper, we will propose a camera-model identification method based on two-step Markov process under seven direction conditions. To reduce algorithm complexity, a threshold-ing technology will be used. Besides that, we will combine it with detection method based on CFA artifacts [18]. CFA detection method always works well among the second approaches. Obviously, the hybrid model between these two methods can study camera model-specific more comprehensively, which will bring high detection accuracy theoretically.

Since the hybrid model for statistics classification involves more than one forensics approach, detection feature size must be large. To limit feature dimensions, a feature selection algorithm will be introduced in this paper.

3. Markov Feature

3.1. Difference JPEG 2-D Array

As the final camera output, the quantized block DCT coefficient of image carries all the related information we can get, include ‘digital scene content’, and the ‘potential detail information referred to model identification’. However, scene is the ‘strongest’ information within an image. If we extract statistical features directly from quantized block DCT coefficient, it is more possible to get the statistics of ‘scene content’ rather than ‘potential model information’. To weaken the impact of ‘scene content’, the common solution is extracting statistics from the difference between original image and its approximate version. In our work, it is the difference between elements and its corresponding neighbors in JPEG 2-D array. Here, JPEG 2-D array is the absolute value of quantized block DCT coefficients, and the difference image is named as difference JPEG 2-D array [13]. There are three reasons for us to get the difference from JPEG 2-D array instead of quantized block DCT coefficients directly [13], more obvious zig-zag scanning characteristic, dynamic range reduction, less outline and edge information of image content.

In this paper, difference JPEG 2-D array is defined as the difference between an element and two-steps element neighbors in the JPEG 2-D array. We assume there have four basic directions from an element to one of its neighbors, horizontal, vertical, diagonal, and minor diagonal. As can be seemed in Fig. 1, if we marked the initial element as star; along basic directions, four elements can be found as its one-step element neighbors, marked as hollow; and so forth, seven elements can be considered as its two-step element neighbors, marked as solid circles. The vectors from star to solid circles can represent seven directions respectively, which we will use to calculate difference JPEG 2-D array later.

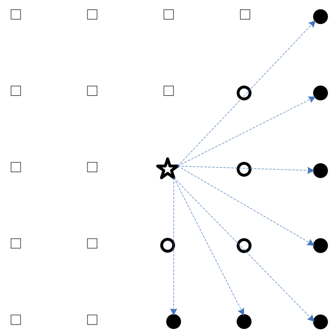

Figure 1. Seven Directions Derivate from 2-step Distance

After seven directions were defined as Figure 1, the difference JPEG 2-D array along seven directions can be calculated as equal (3.1) to equal (3.7) respectively, which the JPEG 2-D array of image is denoted by $F(u,v)(u \in [1,S_u], v \in [1,S_v])$.

$$F_{d1}(u,v) = F(u,v) - F(u,v+2) \tag{3.1}$$

$$F_{d2}(u,v) = F(u,v) - F(u+1,v+2) \tag{3.2}$$

$$F_{d3}(u,v) = F(u,v) - F(u+2,v) \tag{3.3}$$

$$F_{d4}(u,v) = F(u,v) - F(u+2,v+1) \tag{3.4}$$

$$F_{d5}(u,v) = F(u,v) - F(u+2,v+2) \tag{3.5}$$

$$F_{d6}(u,v) = F(u+1,v) - F(u,v+2) \tag{3.6}$$

$$F_{d7}(u,v) = F(u+2,v) - F(u,v+2) \tag{3.7}$$

Where S_u and S_v is the size of the JPEG 2-D array in horizontal and vertical direction respectively; for difference JPEG 2-D array generation, $u \in [1, S_u - 2], v \in [1, S_v - 2]$ and from F_{d1} to F_{d7} denote the difference along seven directions respectively.

3.2. Two-step Transition Probability Matrix with Threshold Setting

Since the difference JPEG 2-D array can be modeled by Markov random process, and transition probability matrix can characterize the Markov process, we use the 2-step transition probability matrices, which extracted from seven difference JPEG 2-D arrays we mentioned respectively, to build feature collection.

Theoretically, the dynamic range of element value on difference JPEG 2-D array is large. It means the transition probability matrices, which extracted from difference JPEG 2-D array directly, might end up large size. To reduce feature size and computational complexity, a threshold-ing technique is introduced. Firstly, we set a threshold value T; secondly, in difference JPEG 2-D arrays, only the elements, which are in the range of –T to T, are considered. The elements, which are out of this range, will be replaced by –T or T. After this threshold-ing setting, the dimensionality of every transition probability matrix will be limited as $(2T+1)\times(2T+1)$. The elements of seven matrices associated with seven difference JPEG 2-D arrays can be calculated by following equals (3.8) to equals (3.14).

$$p\{F_{d1}(u,v+2) = n \mid F_{d1}(u,v) = m\} = \frac{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d1}(u,v) = m, F_{d1}(u,v+2) = n)}{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d1}(u,v) = m)} \tag{3.8}$$

$$p\{F_{d2}(u+1,v+2)=n\mid F_{d2}(u,v)=m\}=\frac{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d2}(u,v)=m,F_{d2}(u+1,v+2)=n)}{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d2}(u,v)=m)} \tag{3.9}$$

$$p\{F_{d3}(u+2,v)=n\mid F_{d3}(u,v)=m\}=\frac{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d3}(u,v)=m,F_{d3}(u+2,v)=n)}{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d3}(u,v)=m)} \tag{3.10}$$

$$p\{F_{d4}(u+2,v+1)=n\mid F_{d4}(u,v)=m\}=\frac{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d4}(u,v)=m,F_{d4}(u+2,v+1)=n)}{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d4}(u,v)=m)} \tag{3.21}$$

$$p\{F_{d5}(u+2,v+2)=n\mid F_{d5}(u,v)=m\}=\frac{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d5}(u,v)=m,F_{d5}(u+2,v+2)=n)}{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d5}(u,v)=m)} \tag{3.32}$$

$$p\{F_{d6}(u,v+2)=n\mid F_{d6}(u+1,v)=m\}=\frac{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d6}(u+1,v)=m,F_{d6}(u,v+2)=n)}{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d6}(u+1,v)=m)} \tag{3.43}$$

$$p\{F_{d7}(u,v+2)=n\mid F_{d7}(u+2,v)=m\}=\frac{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d7}(u+2,v)=m,F_{d7}(u,v+2)=n)}{\sum_{v=1}^{S_v-2}\sum_{u=1}^{S_u-2}\delta(F_{d7}(u+2,v)=m)} \tag{3.54}$$

Combing the elements of seven transition probability matrices together, we will have $7\times(2T+1)\times(2T+1)-D$ feature vectors at last. In other words, the chosen T value will affect detection capability and computational complexity directly. This Markov transition probability matrix extracting method is similar as a part of feature extracting in forensics method [16], but without average algorithm. The whole seven matrices elements are used to complete classification. Hence, in our experiment, we set the threshold T equal to 1, which means we get 63 elements to build Markov features in total.

4. CFA Feature

The CFA feature extracting method we use here is from CFA based forensics approach [18]. Digital camera always place color filter array (CFA) before sensor, which has same resolution as camera sensor. It makes each sensor pixel can only get one color component. After that, a color interpolation algorithm will be introduced to recover the lack color components for every pixel. Three or four color components already can present approximate real color. Each CFA pixel is a mini single color filter; the array has its periodic and certain pattern. Because different camera manufactures or models possibly use different CFA patterns and associate interpolation algorithms, the artifacts caused by CFA and interpolation algorithm can reflect model-specific difference to some extent. Previous work shows that camera inside color interpolation process can be regarded as a weighted average processing, which has low-pass nature [17]. Theoretically, the interpolated color components should be smoother than other parts statistically. Therefore, the ratio of statistics between interpolated part and original part can reflect different interpolation characteristics under same CFA pattern. Furthermore, for camera model detection, source CFA pattern of test image is unknown, but we can increase the chance of hitting correct setting by calculating above estimation ratio under several common hypothesis CFA patterns. The other thing is camera-specific statistics is possible be affected by image content intensely, it is better to extract statistics from image sensor noise than original image data directly. According to above analysis, a CFA artifacts measure feature set can be described as equals (4.1).

$$\max\left(\frac{stat(N_{p_i}{}^{r})}{stat(N_{p_i}{}^{e})},\frac{stat(N_{p_i}{}^{e})}{stat(N_{p_i}{}^{r})}\right)\quad i=1,\ldots,n \tag{4.1}$$

Where $N_{p_i}{}^{r}$ denotes the original part of image noise under the i^{th} hypothesis CFA patterns; $N_{p_i}{}^{e}$ denotes the interpolated part of image noise under the i^{th} hypothesis CFA patterns; $stat(\square)$ denotes statistics extraction. Finally, 69-D features will be extracted to capture CFA artifacts brought by camera model-specific, more details can be found in [18].

5. Experiment

In our paper, images from seven models in 'Dresden Image Database' [14] have been chosen as experiment samples (Only images taken from more than one device per model are suitable for model detection). Associated information is shown in Table 1.

Table 1. Camera Model

No.	model	Device num/model	Image num/model	Image resolution	Image format
1	CanonIxus70	3	567	3072×2304	JPEG
2	CasioEXZ150	5	925	3264×2448	JPEG
3	FujiFirmFinePixJ50	3	630	3264×2448	JPEG
4	NikonCoolPixS710	5	925	4352×3264	JPEG
5	NikonD70s	2	367	3008×2000	JPEG
6	NikonD200	2	752	3872×2592	JPEG
7	KodakM1063	5	2391	3664×2748	JPEG

Before classification, images are blocked to increase the number of classifying samples and unify sample size; we extract four 512×512 sub-blocks from center of quantized JPEG coefficients directly.

According to the feature generation process mentioned above, 63-D two-step Markov features are extracted from each sub-block. We use SVM classifier [15] to do model detection. The above seven models are used to do model detection. 90% of images are randomly chosen for training and rests of them are used for testing. Our random choosing is controlled to ensure every sub-block in training part and testing part is not from same image. And classification is performed 20 times. The detection result is presented in table 2. The average detection accuracy of 69-D Markov feature is 99.49%.

Table 2. Detection Accuracy Percentage of 63-D two-step Markov Feature based Method (value below 0.05 are denoted as * for instead, blank denotes 0)

model	1	2	3	4	5	6	7
CanonIxus70	99.85			0.11		*	
CasioEXZ150		99.76	0.09	0.12	*	*	
FujiFirmFinePixJ50	*		99.88	0.08	*		
NikonCoolPixS710	0.09	0.15	*	99.55	0.16	*	
NikonD70s			0.24	0.27	98.50	0.99	
NikonD200	*			*	1.05	98.92	
KodakM1063	*			*			99.98

For, CFA feature extraction, we first decompress JPEG image to RGB image, then extract four 512×512 sub-blocks from center of RGB coefficients. According to the above feature extraction method, 69-D CFA features are extracted from each sub-block.

Using the same classification processing, the detection result of 69-D CFA feature based method is obtained, shown in table 3. Combining 63-D Markov features and 69-D CFA features, we can get our final 132-D hybrid features, and its detection result is presented in Table 4. The detection accuracies of 63-D CFA features and 132-D hybrid features are 99.32% and 99.83% respectively.

Table 3. Detection Accuracy Percentage of 69-D CFA Feature based Method (value below 0.05 are denoted as * for instead, blank denotes 0)

	1	2	3	4	5	6	7
CanonIxus70	99.65			0.35			
CasioEXZ150		99.88	*		0.11		
FujiFirmFinePixJ50		1.43	98.39		0.12	0.06	
NikonCoolPixS710	0.22			99.76		*	
NikonD70s		0.07	0.31	*	98.98	0.58	*
NikonD200	*		*	*	1.23	98.70	
KodakM1063			0.07	*	*	*	99.87

Table 4. Detection Accuracy Percentage of 132-D Hybrid Feature based Method (value below 0.05 are denoted as * for instead, blank denotes 0)

	1	2	3	4	5	6	7
CanonIxus70	99.96			*			
CasioEXZ150		100					
FujiFirmFinePixJ50			100				
NikonCoolPixS710	*			99.97			
NikonD70s					99.29	0.71	
NikonD200	0.07				0.33	99.60	
KodakM1063						*	99.99

The experiment shows that our method can identify seven models with high detection rate. To further measure the effectiveness of our method, we use 324-D one-step Markov features extracted from Y component [12] to do model detection under the same condition. Fig.2. shows detection accuracy using four algorithms. We can see that in seven models detection, the average detection accuracy of our proposed method is 99.83%, which is obvious higher than previous one-step Markov method.

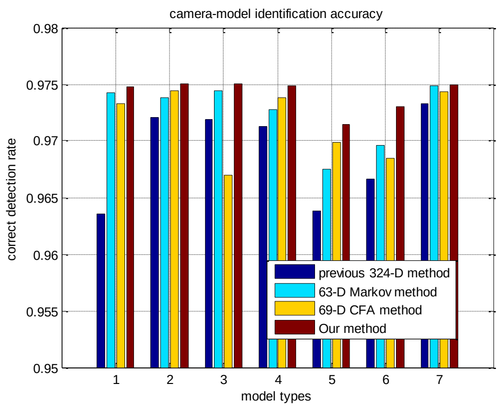

Figure 2. Model Detection Accuracy using Compared Methods

A Minimum redundancy maximum relevance (mRMR) feature selection method is introduced here to decrease our feature dimension. The detection accuracies of feature based method after feature selection are shown in Figure 3. We can see that even only using 40 features after feature selection, the average detection accuracy is 99.58%, which is higher than preview 324-D Markov method. According to the above experiment result, both our proposed method and Markov method works well on seven camera models classification. But our proposed method can performance better even with obvious smaller feature size.

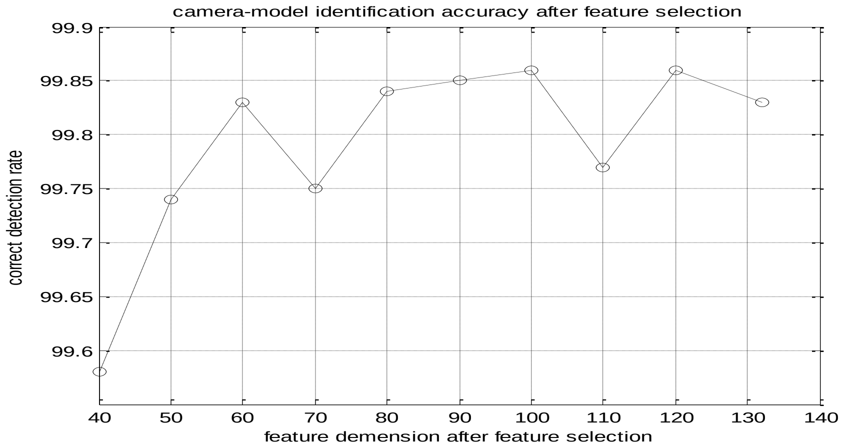

Figure 3. Model Detection Accuracy Using our Method after Feature Selection

6. Conclusion

This paper presents an algorithm for camera-model identification. We propose a hybrid model to distinguish different camera model-specific. Two-step Markov features and CFA features are combined to build detection features. Finally, 132-D features are obtained to do model detection. The experiment result shows that the detection accuracy of our proposed method works well on seven camera models. The average detection accuracy is 99.83%. Even only using 40-D features selected by mRMR method, the detection accuracy still can reach 99.58%. Compared with previous Markov method, our method can have better performance even with obvious smaller feature size

References

[1] J. Lucas, J. Fridrich, and M. Goljan, “Digital camera identification from sensor pattern noise”, IEEE Trans. Inf. Forensics Security, vol. 1, no. 2, (**2006**), pp. 205–214.
[2] M. Chen, J. Fridrich, M. Goljan, and J. Lukáˇs, “Determining image origin and integrity using sensor noise”, IEEE Trans. Inf. Security Forensics, (**2008**), vol. 3, no. 1, pp. 74–90.
[3] C.-T. Li, “Source Camera Identification Using Enhanced Sensor Pattern Noise”, IEEE Trans. Inf. Forensics Security, (2010), vol. 5, no. 2, pp. 280–287.
[4] M. Kharrazi, H. T. Sencar, and N. Memon, “Blind source camera identification”, Proceedings of the International Conference on Image Processing, (**2004**), vol. 1, pp. 709–712.
[5] K. S. Choi, E. Y. Lam, and K. Y. Wong, “Automatic source identification using the intrinsic lens radial distortion”, Opt. Express, vol. 14, no. 24, (**2006**), pp. 11551–11565.
[6] S. Bayram, H. T. Sencar and N. Memon, “Improvements on source camera-model identification based on CFA interpolation”, Proc. of WG. 11.9 Int. Conf. Digital Forensics (**2006**), pp. 24-27.
[7] A. Swaminathan, M. Wu and K. J. R. Liu, “Non-intrusive component forensics of visual sensors using output images”, IEEE Trans. Inf. Forensics Security, vol. 2, no. 1, (**2007**), pp. 91–106.
[8] H. Cao and A. C. Kot, “Accurate detection of demosaicing regularity for digital image forensics”, IEEE Transactions on Information Forensics and Security, vol. 4, (**2009**), pp. 899-910.
[9] M. Kirchner, “Efficient Estimation of CFA Pattern Configuration in Digital Camera Images”, Media Forensics and Security II, Proc. SPIE, vol. 754110, 754111, (**2010**).
[10] O. Celiktutan, B. Sankur, and I. Avcibas, “Blind identification of source cell-phone model”, IEEE Trans. Inf. Forensics Security, vol. 3, no. 3, (**2008**), pp. 553-566.
[11] A. E. Dirik, H. T. Sencar, and N. Memon, “Source camera identification based on sensor dust characteristics”, Proc. of IEEE SAFE, (**2007**), pp. 1-6.
[12] G. Xu, S. Gao, Y. Q. Shi, R. M. Hu and W. Su, “Camera-model identification using Markovian transition probability matrix”, 8th International Workshop on Digital Watermarking, Springer Verlag, (**2009**), pp. 294-307.

[13] Y. Q. Shi, C. Chen and W. Chen, "A Markov Process Based Approach to Effective Attacking JPEG Steganography", Information Hiding 2006 (**2006**), pp. 249-264.
[14] T. Gloe and R. Böhme, "The 'Dresden Image Database' for benchmarking digital image forensics", Proceedings of SAC (**2010**), pp. 1584-1590.
[15] C.-C. Chang and C.-J. Lin, "LIBSVM, a library for support vector machines (2001)", http://www.csie.ntu.edu.tw/˜cjlin/libsvm (**2001**).
[16] S. Gao, R.M. Hu, and G. Tian, "Using multi-step transition matrices for camera model identification", IJHIT, (2012), vol. 5, no. 2, pp. 275-288.
[17] M. Kirchner, "Efficient Estimation of CFA Pattern Configuration in Digital Camera Images", Media Forensics and Security II, Proc. SPIE, vol. 754110, (**2010**).
[18] S. Gao, G. S. Xu, and R. M. Hu, "Camera model identification based on the characteristic of CFA and interpolation", IWDW11, LNCS, vol. 7128, (**2011**), pp. 268-280.
[19] M. Mohamed Sathik and S. S. Sujatha, "Wavelet Based Blind Technique by Espousing Hankel Matrix for Robust Watermarking", IJAST, vol. 26, (**2011**), pp. 57-72.
[20] V. Saxena, P. Khemka, A. Harsulkar and JP Gupta, "Performance Analysis of Color Channel for DCT Based Image Watermarking Scheme", IJSIA, vol. 1, no. 2, (**2007**), pp. 41-46.
[21] J.-C. Liu, C.-H. Lin, W.-S. Lai and Y.-W. Lee, "A Robust Watermark Scheme for Copyright Protection", IJSEIA, vol. 2, no. 4, (**2008**), pp. 21-30.

