CAMERA/MOBILE PHONE SOURCE IDENTIFICATION FOR DIGITAL FORENSICS*

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ABSTRACT

Digital forensics has lately become one of the very important applications to identify the characteristics and the originality of the digital devices. This study has focused on analyzing the relationship between digital cameras and the photographs by using the support vector machine (SVM). Based on the fact that the internal imaging formation algorithms of the cameras are different from one manufacturer to another, our approach first calculates the characteristic values of the images taken by different cameras in conjunction with image processing techniques and data exploration methods. The training and categorization procedures of the image characteristic values are further conducted through SVM to identify the source camera of the images. Based on SVM's ability to distinguish cameras of different brands, this study also examines whether the method can differentiate cameras of the same brand, or even the popular mobile phones with camera. The experiment results demonstrate that our approach can achieve higher identification rate for camera and mobile phone sources than the results from other literatures.

Index Terms—cameras, correlation, feature extraction.

1. INTRODUCTION

Widespread use of the Internet changes the way people acquires and uses information. Many applications are made possible through the use of large amount of digital images. In the field of digital forensic, development related to digital images has been growing [1-4]. M. Kharrazi, et al.[1] and Tsai[4] uses features and classifier to identify camera sources. A. Swaminathan, et al. [3] developed a non-intrusive forensic framework which provides evidence for analyzing infringement technology and evolution for visual sensors.

The purpose of this study therefore is to acquire image characteristics and apply appropriate categorization methods to determine source of the camera or mobile phone with camera. Unlike the findings in [4] where the high correlation exists among the same camera brand during the identification, this study develops the algorithm to reduce the confusion for the same brand with different model.

This paper will be organized as follows. The details of the approach will be explained in Section 2. Section 3 will show the experiment with discussion and conclusion is in Section 4.

2. THE APPROACH

To identify the source camera of a certain image, a set of image features should be obtained about the characteristics of the camera. Although the color image formation processes are different among different manufacturers, the output image is greatly influenced by the following three factors:

- Color Features

Color Features refer to image-color-related characteristics that have not been processed through signal conversion. These characteristics generally include the mean value, correlation coefficient, proximity distribution center and energy ratio[2].

- Quality Features

Besides the Color Features, the photographing qualities of different cameras are also different. Normally we can differentiate the quality discrepancies between images captured by different cameras with naked eyes. We utilize Image Quality Metrics (IQM) [2] to describe these visual differences.

For some multimedia images of low bit rate, therefore, a set of image characteristic indexes has been developed. Based on human being's physical senses, it can be divided into six categories: a. Pixel Difference-based; b. Correlation-based; c. Edge-based; d. Spectral-based; e. Context-based; f. Human visual system (HVS)-based features.

Some of the indexes here are for dynamic images. Therefore, we select a, b and d, the measurement indexes for static images, as our image forensic indexes.

- Image Characteristics of Frequency Domain

After converting images from the spatial domain to the frequency domain, the transform approach filters different frequencies of the image and generates many frequency bands. In this study, we adopt the Wavelet Transform method for calculating wavelet domain statistics.

In comparison with the research approach of the reference [1, 4], this study adds the SVM optimal parameter set-

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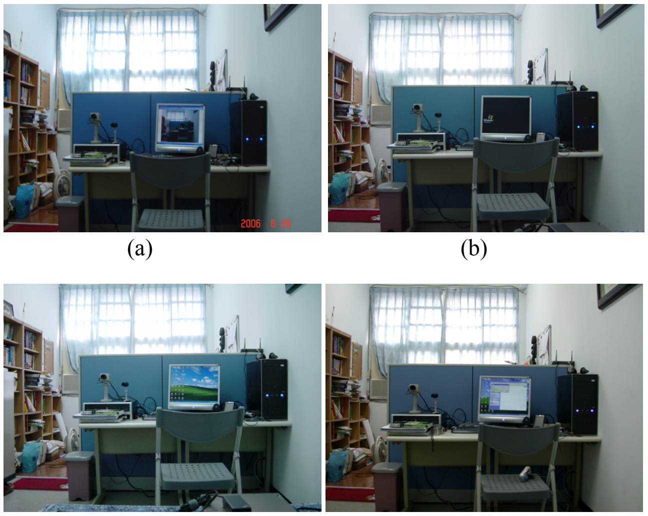
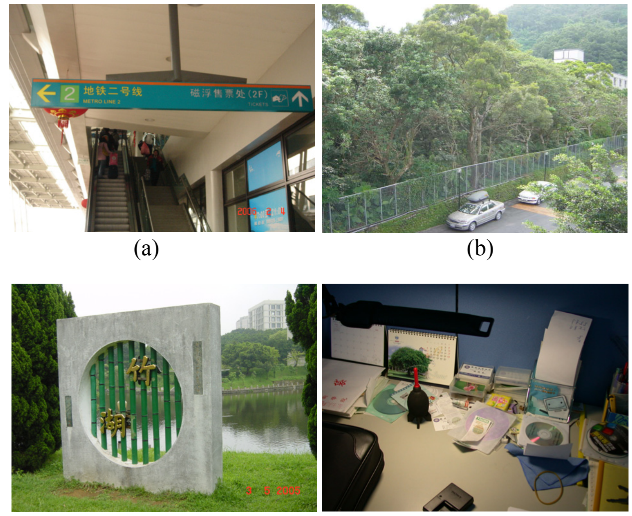


(a) (b) (c) (d)

Fig. 1. Image samples (a)-(d) with similar content



(a) (b) (d) (d)

Fig. 2. Image samples (a)-(d) with dissimilar content

ting search step to enhance the identification rate. Detailed steps are as follows: First, the image contents captured by different cameras are collected. The resolution of the image size is at least 1600×1200. Next, the image processing technique is employed to compute the characteristic values of the image. The images are randomly divided into SVM Train Data and SVM Test Data. SVM Train Data is transmitted into LibSVM software [5] for establishment of the Train Model. The optimal parameter search program is then employed for prediction and classification, and the completion of the optimal parameter distribution diagram. Finally, the optimal parameter is selected and inserted into SVM for forensic analysis. The identification rate of the data is therefore obtained. To reduce forensic error due to the random sampling, we repeat the above steps 10 times to get the average identification rate.

3. EXPERIMENTS AND DISCUSSION

The experiment of this study is made up of two parts. The first part involves cross-examination of three main components: image content, image pattern and brand with model. We design three different cases and examine the impact of each one on the identification ratio. The feature of the second part lies in the assumption that the contents captured by different cameras are completely different. In accordance with the brand, model, and sensory element, we design three cases to compare the results as well.

In the first case, we use four cameras (SONY-T7, SONY-P9, SONY-P1 and Nikon-E995) to take 150 pictures each of highly similar contents. An example is shown in Fig. 1(a)-(d) Out of the 150 pictures, 60 are used as Train Data and 90 are used as Test Data for verification in order to explore whether image similarity enhances or reduces the identification rate. In Table I, the identification rate is as high as 100%. Therefore, the extremely high image content will enhance the identification rate which is higher than the literature results from [1, 4]. In practical, we rarely have this kind of opportunity while testing different cameras. Therefore, in order to verify whether content similarity affects the identification ratio, we use the same camera with different content as shown in Fig. 2(a)-(d). The data from Table 2 shows the identification ratio decreases as expected and the degree of content similarity does affect the identification ratio to certain extent.

From the experiments above, we reach the initial conclusion that content similarity affects the identification ratio. That indirectly explains the importance of selecting the SVM Train Data during the testing. Since high similarity image content will impact the identification ratio, will the three image patterns employed by this study cause misjudgments? To address this issue, we take a set of pictures of high similarity and a set of pictures of low similarity each

Table 1. Identification results of 4 different cameras with high similar image content

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	100	0	0	0
	SONY-P1	0	100	0	0
	SONY-P9	0	0	100	0
	SONY-T7	0	0	0	100

Table 2. Identification results of 4 different cameras with dissimilar image content

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	96.1	0	3.6	0.3
	SONY-P1	0	94.3	1.9	3.8
	SONY-P9	2.1	7.1	89.0	1.8
	SONY-T7	0.2	4.1	2.9	92.8

Table 3. Identification results of 4 different cameras with similar and dissimilar image content

		Predicted(%)							
		Nikon-E995		SONY-P1		SONY-P9		SONY-T7	
		Similar	Dissimilar	Similar	Dissimilar	Similar	Dissimilar	Similar	Dissimilar
Actual	NikonE995 (Similar)	100	0	0	0	0	0	0	0
	NikonE995 (Dissimilar)	3.2	92.2	0	0	0	3.9	0	0.7
	SONYP1 (Similar)	0	0	100	0	0	0	0	0
	SONYP1 (Dissimilar)	0	0	3.4	89.6	0	3.3	0	3.7
	SONYP9 (Similar)	0	0	0	0	100	0	0	0
	SONYP9 (Dissimilar)	0	1.4	0.4	5.1	1.4	89.0	0.1	2.4
	SONYT7 (Similar)	0	0	0	0	0	0	100	0
	SONYT7 (Dissimilar)	0	0	0	4.3	0.4	1.8	0.6	92.9

for classification. From Table 3, we discover that the difference occurs due to the Train data selected by SVM and this outcome reveals the possible limitation which is expected.

After verification of the fact that image similarity will definitely affect the identification ratio, we then examine whether the image features will also influence the identification ratio. In reference [1], the image can be divided into 3 categories and 33 features. Next we explore the relationship of image feature category, image content and identification ratio. The experiment is based on the assumption that among the 4 cameras, only images of low content similarity are used with only 1 out of the 3 categories selected for SVM classification in order to observe which category has greater impact on the identification ratio. From Table 4, we can observe that no single category can obtain good identification ratio even the wavelet frequency domain features show higher values.

To make a fair comparison, we repeat the previous experiment except that the image data with high content similarity. Tables 5 indicates that high content similarity contributes to high identification ratios for each case. Therefore, each pattern could be good enough for identification purpose. While image content is different, all 3 category features should be included in SVM for consideration.

According to [4], we learn that it is more difficult to deal with the same brand with different models. It is possible that the same-brand factor will lower the classification identification ratio if the key image processing components are alike. To test the capability of the method proposed by this study, we use 7 CCD cameras of the same brand but different models for identification test. From Table 6, it shows

Table 4. Accuracy rate for each category with dissimilar image content of 4 different cameras (a) Color Feature (b) Image Quality Feature (c) Wavelet Domain Feature

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	52.0	13.9	21.3	12.8
	SONY-P1	3.5	72.9	17.3	6.3
	SONY-P9	8.4	26	57.9	7.7
	SONY-T7	14	12.1	8.1	65.8

(a)

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	65.9	8.3	7.3	18.5
	SONY-P1	7.1	64.5	8.3	20.1
	SONY-P9	4	12.4	57.7	25.9
	SONY-T7	14.7	14.5	12.1	58.7

(b)

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	100	0	0	0
	SONY-P1	0.4	96.7	2.9	0
	SONY-P9	6.3	6.6	86.3	0.8
	SONY-T7	4	15.7	2.5	77.8

(c)

Table 5. Accuracy rate for each category with similar image content of 4 different cameras (a) Color Feature (b) Image Quality Feature (c) Wavelet Domain Feature

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	100	0	0	0
	SONY-P1	0	97.7	2.3	0
	SONY-P9	0	0.2	99.8	0
	SONY-T7	0	0	0	100

(a)

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	100	0	0	0
	SONY-P1	0	100	0	0
	SONY-P9	0	0.6	99.4	0
	SONY-T7	0.3	0.2	0	99.5

(b)

		Predicted (%)			
		Nikon -E995	SONY -P1	SONY -P9	SONY -T7
Actual	Nikon-E995	100	0	0	0
	SONY-P1	0	100	0	0
	SONY-P9	0	0	99.1	0.9
	SONY-T7	0	0	0.2	99.8

(c)

To further evaluate the impact of camera brand, model and quantity on the identification ratio, we next examine key components of the camera to see if the image sensor also influences the identification ratio. Besides regular digital camera, the mobile phones with camera become quite popular image acquisition tools lately. However, the sensory element of regular cameras is mainly CCD while the sensory element of camera-type mobile phones is mostly CMOS.

In the next experiment, 6 devices (3 regular cameras and 3 mobile phones with camera) of the same brand are used to take 150 photos each in which 60 are Train Data and 90 are Test Data. Table 7 shows the application of different image acquisition equipments (camera or mobile phone) with different sensory elements (CCD or CMOS) can still achieve good identification ratio among the test.

This study has employed various experiment attributes to analyze the impact factors, such as image content, image pattern, camera brand/model, sensory element and number of classification cameras for the identification ratio. From the experiment results, this approach shows high identification ratio and indicates the method employed by this study can effectively identify the source camera of the image. On the other hand, some research constraints have also been identified. For instance, during the first part of the experiment we are sure that under the ideal condition of extremely high content similarity we can have an identification ratio of 100% every time. But other experiment outcomes reveal we are unable to identify the fact that the different contents captured by the same digital camera are in fact from the same camera even the identification ratio is already higher than the results from [1, 4]. The experiment outcomes help us realize the fact that the impact of content similarity on the identification ratio is very significant. In addition, we observe the fact that the more digital cameras are included in the identification test, the more the identification ratio will decrease due to the statistic errors. How to deal with these limits is an important issue for future studies.

Table 6. Identification results of 7 different cameras of the same brand with dissimilar image content.

SONY		Predicted(%)						
		N1	P1	P8	P9	T1	T3	T7
Actual	N1	93.3	0	0	1.1	0.7	0.9	0
	P1	2.8	93.7	0.2	1	0.1	2	0.2
	P8	0.2	1.1	97.8	0	0.9	0	0
	P9	1.2	0.4	0	97.4	0.2	0	0.8
	T1	2.2	0.2	0.4	0	96.3	0.9	0
	T3	1.7	3.6	0.1	1.1	0.5	88.9	4.1
	T7	0	0	0	0.2	0	1.7	98.2

(a)

Table 7. Identification results of 3 different cameras and 3 different mobile phones with dissimilar image content.

SONY		Predicted(%)					
		K600 (CMOS)	K700 (CCD)	K750 (CMOS)	P1 (CCD)	P9 (CCD)	T7 (CCD)
Actual	K600 (CMOS)	97.8	0	1.1	1.1	0	0
	K700 (CCD)	0	96.7	2.2	1.1	0	0
	K750 (CMOS)	0	1.1	98.9	0	0	0
	P1 (CCD)	0	0	0	100	0	0
	P9 (CCD)	0	0	0	0	98.9	1.1
	T7 (CCD)	0	0	0	0	2.2	97.8

(b)

4. CONCLUSION

This study has focused on analyzing the relationship between digital cameras and the photographs by using the support vector machine. Our approach utilizes the optimal parameter search program in SVM for prediction and classification which results better identification precision rate. Based on SVM's ability to distinguish cameras of different brands, this study also examines whether the method can differentiate cameras of the same brand with different models, or even the popular mobile phones with camera. In contrast with the same brand and model employed in reference [4], the implementation of the experiment steps and technique of this study in different environments and scenes enhances the identification ratio which indicates the strength of the forensic research proposed by this study.

5. REFERENCES

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