USING IMAGE FEATURES TO IDENTIFY CAMERA SOURCES

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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 associated images. Digital image processing technology has been applied with data mining method to get images' features. Those features were trained and classified to identify the camera sources from the images. In addition, the identification features were further categorized for improvements, based on the analyses, to enhance the precision rate of the identification. This research also compared not only cameras of different brand, but also those of the same manufacturer with similar models. This research has found that the feature based approach has better performance to distinguish the camera sources among brands. Further findings are discussed and suggested for the potential limit of the identification methods in real applications.

1. INTRODUCTION

With the aids of the inexpensive digital and multimedia devices, digital images have been created in an unexpected high speed worldwide. In the past, an image or photograph could be generally accepted in court as a "proof of evidence". However, the creation and manipulation of digital images is comparably simple with the help of powerful image processing tools. Therefore, can digital images still be trusted as the legal photographic evidence? Or, is the camera used to take the photo as it is said?

The investigation and law enforcement agencies constantly face difficulties as the situation mentioned above since they need identification techniques. Although digital watermarks can be used to identify images, most digital images do not contain those marks. This situation won't be changed easily in the near future. Hence, it is necessary to develop techniques that help us to identify the sources and authenticity of digital images.

Image forensics can be applied to serve the identification purpose which covers a wide array of complex and extensive researches. Although the information about the camera model, brand, date and time of pictures can be saved in the JPEG header, those information could be modified and cause the problem of trusty. In this study, the main focus will be addressed is to identify the source of the camera based on the given digital images. There have been some prior studies to identify the source cameras with a given image, such as defective pixel location [1]. Nevertheless, this approach fails since the new digital camera makers have been able to eliminate almost all the onboard defective pixels and post-process the final images. Advanced research has been done by M. Kharrazi, H.T. Sencar, and N. Memon [2]. This study further investigates the relationship among the image features of [2] with pre-analysis for the classifiers in order to improve the precision rate.

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 two factors:

- Color Filter Array (CFA) configuration and demosaicing algorithm.
- The color processing and transformation.

Regardless of the original image content, certain property and patterns will be embedded in the image when the digital contents in RGB band are processed. In order to capture the image characteristics between images from different cameras, each camera's images were processed and their image features were documented for comparison. In consequence, a forecasting model was built for image identification by classifying these image features.

This study has used a total of 33 features to identify the source cameras [2][4]. In this research, these features were grouped into three categories: color features, image quality features and wavelet domain features. Each feature is designated with a capitalized letter: "C" for color features, "Q" for image quality features, and "W" for wavelet domain features. These features are detailed in the following paragraphs.

- **Color Features**

a. *Average Pixel Value*: The measure is based on the grayscale assumption, which states that the average values in RGB channels of an image should average to gray, assuming that the image has enough color variations. Thus the features are the average values of the 3 RGB channels, C1, C2 and C3.

b. *RGB Pairs Correlation*：The measure attempts to capture the relationship between different color bands. There are 3 correlation pairs, namely RG(C4), RB(C5), GB(C6).

c. *Neighbor Distribution Center of Mass*：This measure is calculated for each color band separately (C7, C8 and C9). Firstly, the number of pixel for each pixel value is calculated. Secondly, the numbers are transferred to neighbor values where neighbor values are sums of each pixel value's neighbor pixel, which was defined as all pixels that have a difference of value of 1 or -1. Finally, the neighbor values from 0 to 255 are cumulated, and when the cumulated sum reaches half of neighbor values' sum, the pixel value is the "Center of Mass".

d. *RGB Pairs Energy Ratio*：This measure is used in the process of white point correction and mentioned in [1]. There are C10, C11 and C12 values.

- **Image Quality Features**

In order to get more detailed difference of images, the image quality feature [3-4] which includes pixel-difference-based, correction-based and spectral-based measures was adopted. These features are listed as follows.

-Pixel Difference-based：

a. Mean Square Error, MSE, Q1
b. Mean Absolute Error, MAE, Q2
c. Minkowski Difference, Q3

- Correlation-based：

d. Structural Content, Q4
e. Normalized Cross Correlation, Q5
f. Czekonowski Correlation, Q6

- Spectral-based：

g. Spectral Magnitude Error, Q7
h. Spectral Phase Error, Q8
i. Spectral Phase-magnitude Error, Q9
j. Block spectral magnitude error, Q10
k. Block spectral phase error, Q11
l. Block spectral phase-magnitude error, Q12

- **Wavelet Domain Statistic**

An image can be presented not only in the spatial domain, but also in the frequency domain. Wavelet transformation of popular referred 9/7 filters is adopted to transform the image from the spatial domain to the frequency domain and decompose each color band of image into 4 sub-bands. Then, the mean for each of the 3 resulting high frequency sub-bands is obtained. In this category, there are 9 features obtained: W1, W2, W3, W4, W5, W6, W7, W8, W9.

The classifying software adopted in this research was LibSVM[5]. Support Vector Machines will help the classification of incoming data and examine the precision rate.

The image data of [2] were tested where Nikon E2100 and Sony P51 cameras are used and the features in each category of features were analyzed. The results are shown in Table I. From Table I, it is clear that the color feature has lower accuracy than other group of features for both cameras. Therefore, the weighting function among the categorized features in the classifier should be evaluated further and more features or other condition could be considered in order to improve the accuracy rate. The possible factors are listed as following:

A. Environmental light－digital cameras adopt different image formation processes under different light environment. For example, the ISO value will be adjusted lower and the noise signal will be restrained in the same time when the pictures are taken outdoors. Therefore, different configurations will influence the formation of images.

B. The configuration of CFA－The factor was discussed in Reference [3-4]. Different cameras have various CFA configurations. However, these configurations are commercially secret with little details and will not be addressed here.

To utilize the findings, the approach of the feature based identification procedures are in following steps which are applied during the simulation of this study:

A. Different cameras were used to take 150 pictures on NCTU campus respectively; 75 of them are outdoor scenes and the others are indoor scenes. The indoor and outdoor scenes are pre-analyzed for classification.

B. Each image feature (C1-C12, Q1-Q12 and W1-W9) was calculated and documented.

C. 30 indoor and 30 outdoor images were randomly selected and used in the classifier design phase. The obtained classifier was then used to classify the rest of the images.

D. The training and testing procedure will continue and the weighting of the three categorized features will be adjusted till the precision rate converged with no further variation.

Table I. Accuracy rate for each category

	Individual identification (%)	
	Nikon	Sony
Color Feature	57.54	55.41
Image Quality Feature	76.33	78.72
Wavelet Domain Feature	90.64	87.23

(a) A photograph from SONY P1

(b) A photograph from Nikon E5000

Figure 1. Image samples at NCTU campus

Table II.(a) Statistics from [2]

		Predicted (%)	
		Nikon	Sony
Actual	Nikon	99.88	0.12
	Sony	2.4	97.6

Table II.(b) Statistics of this study

		Predicted (%)	
		Nikon	Sony
Actual	Nikon	99.76	0.24
	Sony	1.88	98.12

3. EXPERIMENTS AND DISCUSSION

The image vector method is based on the differentiation of embedded image features by different image formation processes in various brands. To test the proposed approach, the image data of [2] is tested and the results are compared. The comparison is tabulated at Table II(a) and II(b). At high identification rate, both feature based methods have comparable statistics. In other words, the cameras used in the above experiments are from different manufactures and it is highly possible that the feature based approach can identify the sources effectively.

Further study is then needed to consider the situation while cameras are from the same brand with different models which generally share similar image formation process. Therefore, Nikon E5000 and SONY P1 were then used in this study since the cameras in [2] are also from both brands. In addition, more testing images were captured on NCTU campus instead of in New York and samples are shown in Figure 1.

Table III. Identification result of 4 different cameras

		Predicted (%)			
		Nikon E5000	Sony P1	Nikon E2100	Sony P51
Actual	Nikon E5000	95.29	0.82	3.15	0.74
	Sony P1	2.47	69.52	1.90	26.11
	Nikon E2100	3.93	1.08	94.12	0.87
	Sony P51	5.14	22.68	4.54	67.64

Testing image data are then grouped together where include total 4 cameras with New York and NCTU campus image content and the identification results by the proposed approach is shown in Table III. From Table III, the identification rate of images taken by Nikon cameras was over 95%, while the results between the two Sony cameras are obviously lower. In order to analyze the internal reciprocal effect between cameras of the same brand, the images were grouped based on the camera brand for further study. The results are shown in Table IV(a)(b).

From Table IV, the results between Sony's cameras are not as good as Nikon's. In other words, the two Sony's cameras have a lower identification ratio where hardware components may be the reason to cause the low numbers. To prove the speculation, the hardware specification of the

Table IV(a). Results between Sony cameras

		Predicted (%)	
		Sony P1	Sony P51
Actual	Sony P1	76.38	23.62
	Sony P51	18.35	81.65

Table IV(b). Results between Nikon cameras

		Predicted (%)	
		Nikon 5000	Nikon 2100
Actual	Nikon 5000	97.13	2.87
	Nikon 2100	3.33	96.67

Table V. Hardware Specification of Sony cameras

	SONY DSC P1	SONY DSC P51	SONY F717
CCD Pixels	3.34 million	2.11 million	5.24 million
CCD size	1/1.8″	1/2.7″	2/3″
A/D Converter	12 bits	12 bits	14 bits
Optical Lens	3X	2X	5X

two Sony cameras are compared and presented in Table V.

From Table V, it is noticeable that SONY DSC-P1 and P51 are both equipped with Sony super-HAD CCD, and are similar in terms of their models. On the contrary, Nikon E5000 is a high-end model while E2100 is comparatively low-end product. Therefore, based on the results, it is the researchers' hypothesis that the results of Sony cameras were affected by the fact that they share the same CCD and the major component between similar models.

In order to prove the hypothesis, another high-end, professional Sony camera F717 was also compared in Table V. It is undoubted that high end product generally has better specification in terms of the image resolution, optical lens and the CCD size.

Supposing that the professional camera has different image formation process from other Sony cameras, 150 pictures were taken by the third Sony camera and compared with the other two. The result is shown in Table VI.

Obviously, with the third Sony camera, P1 and P51 still present reciprocal effects, but the Sony F717 has an identification ratio around 90%. Finally, by comparing all 5 cameras together, the results are presented in Table VII.

The above experiments present several findings:

A. Although the identification rate of Sony F717 is around 90%, it is still not as good as the number made by the comparison between cameras of different brands, i.e., Nikon.

B. Furthermore, the identification method is affected by similar camera models or the same CCD. In other words, if cameras are of the same brand and belonging to the same product series, the identification results between them will be affected since the core component might be identical.

Table VI. Identification results of Sony cameras

		Predicted (%)		
		Sony P1	Sony P51	Sony F717
Actual	Sony P1	74.81	22.71	2.48
	Sony P51	20.67	78.26	1.07
	Sony F717	4.68	4.88	90.44

Table VII. Identification results of Sony and Nikon cameras

		Predicted(%)				
		Nikon E5000	**Sony P1**	**Nikon E2100**	**Sony P51**	**Sony F717**
Actual	**Nikon E5000**	94.43	0.72	2.65	0.19	2.01
	Sony P1	3.78	68.87	4.19	20.44	1.72
	Nikon E2100	3.57	1.38	93.18	1.71	0.16
	Sony P51	4.79	20.83	2.84	67.48	4.06
	Sony F717	3.13	2.37	0.43	3.96	90.1

In addition, many manufactures build the production line either using the OEM model or purchasing the modules from the key component suppliers. It turns out several brand may share the similar critical components which in turn influence the identification results. A more precise comparison is needed if more camera models from different brands are available. However, current results have shown the feature based approach could identify the camera source effectively across brands even the potential limits still exist.

4. CONCLUSION

This study has focused on analyzing the identification of the camera sources. Digital image processing technology has been applied and the image features were trained and classified in order to identify the camera sources effectively. Different cameras and scene content are used for the identification experiments. It has shown that no matter what content an image contains, using image feature vector can distinguish the images source cameras effectively across the brands. In addition, each feature is analyzed in order to improve the identification precision rate. Finally, the potential limits of the identification method are discussion in this study and further experiments are needed for more precise results.

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