BLIND SOURCE CAMERA IDENTIFICATION

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ABSTRACT

An interesting problem in digital forensics is that given a digital image, would it be possible to identify the camera model which was used to obtain the image. In this paper we look at a simplified version of this problem by trying to distinguish between images captured by a limited number of camera models. We propose a number of features which could be used by a classifier to identify the source camera of an image in a blind manner. We also provide experimental results and show reasonable accuracy in distinguishing images from the two and five different camera models using the proposed features.

1. INTRODUCTION

In the analog world, an image (a photograph) has generally been accepted as a "proof of occurrence" of the depicted event. In today's digital age, the creation and manipulation of digital images is made simple by digital processing tools that are easily and widely available. As a consequence, we can no longer take the authenticity of images, analog or digital, for granted. This is especially true when it comes to legal photographic evidence. *Image forensics*, in this context, is concerned with determining some underlying fact about an image. For example image forensics is the body of techniques that attempt to provide authoritative answers to questions such as:

- Is this image an "original" image or was it created by cut and paste operations from different images?
- Was this image captured by a camera manufactured by vendor X or vendor Y?
- Did this image originate from camera X as claimed? At time Y? At location Z?
- Does this image truly represent the original scene or was it digitally tampered to deceive the viewer? For example, was this coffee stain actually a blood stain that was re-colored?
- Was this image manipulated to embed a secret message? That is, is this image a stego-image or a cover-image?

This work was supported by AFRL Grant No. F30602-03-C-0091.

The above questions are just a few examples of issues faced routinely by investigation and law enforcement agencies. However, there is a lack of techniques that could help them in finding authoritative answers. Although digital watermarks have been proposed as a tool to provide authenticity to images, it is a fact that the overwhelming majority of images that are captured today do not contain a digital watermark. And this situation is likely to continue for the foreseeable future. Hence in the absence of widespread adoption of digital watermarks, we believe it is imperative to develop techniques that can help us make statements about the origin, veracity and nature of digital images.

The problems faced in Image Forensics are extremely difficult and perhaps even hard to formulate in a clean and simple manner. In this paper we look at one of the questions above, that is, given an image can we determine the model of the digital camera that was used to capture the image. This is a question that could be often faced during an investigation. Although information about the camera model, type, date and time of the picture are all saved by the camera in the header of the JPEG image, it is not possible to authenticate them. There has been some prior work on identifying the camera used in acquiring a given image [1]. The identification is based on camera characteristics such as defective pixel locations, noise level, image format, and image headers. However such approach is different from the proposed technique in this paper, since it requires the original camera used in image acquisition for evaluation.

The rest of this paper is organized as follows. We start by giving a brief introduction to digital cameras in Section 2. In Section 3, we propose an approach based on feature extraction and classification for the camera source identification problem by identifying a list of candidate features. Experimental results for the two camera case are provided in Section 4. We discuss future work and conclude in Section 5.

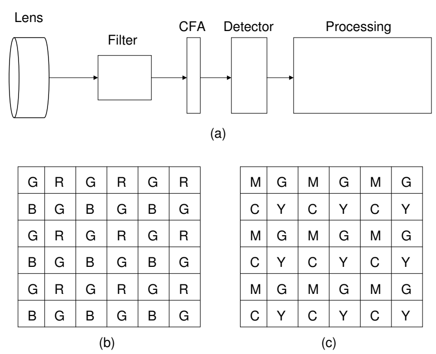

Fig. 1. (a) Major stages of processing in a camera pipeline. (b) CFA pattern using RGB values. (c) CFA pattern using YMCA values

2. DIGITAL CAMERAS

Although much of the details on the camera pipeline are kept as proprietary information of the manufacturer, the general structure and sequence of stages in the camera pipeline seem to be the same in all digital cameras. To set the context for the work presented in later sections, in this section we briefly review the more important stages in a digital camera pipeline. It should be noted that most of the discussion in this chapter is inspired from the introduction to digital cameras by Adams et. al. [2].

The basic structure of a digital camera pipeline can be seen in figure 1(a). After light enters the camera through the lens, a set of filters are employed, the most important being an anti-aliasing filter. The CCD detector is the main component of a digital camera. The detector measures the intensity of light at each pixel location on the detectors surface. In the ideal case, a separate CCD would be used for each of the three color (RGB) channels, but then the manufacturing cost would be quite high. A common approach is to use only a single CCD detector at every pixel, but partition it's surface with different spectral filters. Such filters are called Color Filter Arrays or CFA. Shown in part (b) and (c) of Figure 1 are CFA patterns using RGB and YMCG color space respectively for a 6×6 pixel block. Looking at the RGB values in the CFA pattern it is evident that the missing RGB values need to be interpolated for each pixel. There are a number of different interpolation algorithms which could be used and different manufacturers use different interpolation techniques.

After color decomposition is done by CFA, a detector is used to obtain a digital representation of light intensity in each color band. Next a number of operations are done by the camera, these operations are depicted by the big processor block shown in the figure 1, which include color interpolation as explained before, gamma correction, color processing, white point correction, and last but not least compression. Although the operations and stages explained in this section are standard stages in a digital camera pipeline, the exact processing detail in each stage varies from one manufacturer to the other, and even in different camera models manufactured by the same company. In the next section we will introduce a number of measures which try to capture these differences, and help us in classifying the images originating from a number of cameras.

3. IDENTIFYING MEASURES

One approach to the camera model identification problem is to determine a set of features that designate the characteristics of a specific digital camera, and then use those features to classify obtained images as originating from a specific camera. Although the color image construction process may vary extensively within different makes of digital cameras [2], however, it is our belief that the output image is effected greatly by the following two components:

1. CFA configuration and the demosaicing algorithm
2. The color processing/transformation

As a result of such processing the signal content of the RGB bands will exhibit certain traits and patterns regardless of the original image content. In order to capture the differences in the underlying color characteristics for different cameras we would need to examine the first, second, and possibly higher order statistics of the digital images produced by these cameras. Below we propose a total of 34 features as candidates that would aid in the classification of cameras by make and model:

- *Average pixel value* This measure is based on the *gray world assumption*, which states that the average values in RGB channels of an image should average to gray, assuming that the images has enough color variations. Thus the features are the mean value of the 3 RGB channels (3 features).
- *RGB pairs correlation* This measure attempts to capture the fact that depending on the camera structure, the correlation between different color bands could vary. There are 3 correlation pairs, namely RG, RB (3 features).
- *Neighbor distribution Center of mass* This measure is calculated for each color band separately by first calculating the number of pixel neighbors for each pixel value, where a pixels neighbor are defined as all pixels which have a difference of value of 1 or -1, from

the pixel value in question. The obtained distribution gives us an indication of the sensitivity of the camera pipeline to different intensity levels. We have seen that for a similar image two different cameras have a very similar distribution but one is the shifted version of the other. So we calculated the center of mass of the neighborhood plot to catch that shift as a measure (3 features).

- *RGB pairs energy ratio* is important because it is used in the process of white point correction which is an integral part of a camera pipeline. The calculated features (3 features) are: $E_1 = \frac{|G|^2}{|B|^2}$, $E_2 = \frac{|G|^2}{|R|^2}$,$E_3 = \frac{|B|^2}{|R|^2}$.
- *Wavelet domain statistics* Inspired by Farid's work [3], we decomposed each color band of the image using separable quadratic mirror filters and then calculated the mean for each of the 3 resulting sub-bands (9 features).

In addition to color features, different cameras produce images of different "quality". For example, we commonly notice quality difference between two camera models when images obtained by them are examined visually. For example images obtained by one camera may be sharper but look darker. On the other hand images obtained by another camera may have better lighting and better color quality but are not as sharp as the images obtained by the fist camera. These visual differences that we commonly see motivated us to employ a set of *Image Quality Metrics* (IQM) as features to aid in distinguishing between cameras.

Image Quality Metrics are of utmost importance in providing quantitative data on the quality of a rendered image [4]. IQM's have also been used previously by Memon et al. [5] in the steganalysis problem to distinguish between a set of clean and stego images. We used the same set of IQM's for our studies in this paper. We can categorize the set of IQM's used into three classes based on how the variation between the filtered and original image is measured (13 features):

- the pixel difference based measures (i.e. mean square error, mean absolute error, modified infinity norm);
- the correlation based measures (i.e. normalized cross correlation, Czekonowski correlation);
- the spectral distance based measures (i.e. spectral phase and magnitude errors).

4. EXPERIMENTAL RESULTS

In order to see the effectiveness of the proposed measures in classifying images originating from a digital camera, we conducted a number of experiments. In the first experiment, two different camera models were used, a Sony DSC-P51 and a Nikon E-2100. Both cameras have a resolution of 2 Megapixels. The pictures were taken with maximum resolution, size of 1600×1200, no flash, auto-focus, and the other settings set to the default values. Pictures were taken from the same scene by the two cameras. This is important since for example if one camera was used to take pictures of natural scenery and one camera was used to take pictures of buildings and urban scenery then we might be really detecting the difference in textures of images and not properties due to the camera source.

Fig. 2. The left image was obtained using the Sony DSC-P51, and the right image was obtained by Nikon E-2100.

A picture data set was made by taking 150 pictures with each camera from both inside the university campus buildings as well as other sceneries in New York City; an example is presented in figure 2. Since the Nikon camera had a slightly wider lens, the lens was slightly zoomed at times in order to get the same picture frame as the Sony camera. Only optical zoom was used so that there would be no effects on any of the proposed measures. After collecting the data set, the proposed measures were calculated for each image. A SVM classifier was used in order to see the effectiveness of the proposed features. There are a number of SVM implementations available publicly, and we have used the LibSvm [6] package. A radial basis kernel was used. The following steps were taken in order to design and test the classifier:

1. $2/5$ of the 300 images were used in the classifier design phase.
2. The obtained classifier was then used to classify the previously unseen $3/5$ of the images.
3. The training and testing steps explained above were repeated 100 times, with a random subset used in each step, in order to see the average classification accuracy.

The average accuracy obtained was 98.73%, and the corresponding confusion matrix could be seen in table 1. In the process of our experiments we also noticed that the quantization table used by each camera was different, further it does also vary from one image to another even with the same camera. Therefore we re-compressed all images with compression quality set to 75, and then recollected the statistics from the images, designed, and trained the classifier again. The average accuracy was 93.42%, the corresponding confusion matrix could be seen in table 2.

Table 1. The confusion matrix for 2 camera identification case.

		Predicted	
		Nikon	Sony
Actual	Nikon	**99.88**	0.12
	Sony	2.4	**97.6**

Table 2. The confusion matrix for 2 camera identification case after re-compressing the images with JPEG compression quality set to 75.

		Predicted	
		Nikon	Sony
Actual	Nikon	**96.08**	3.91
	Sony	9.25	**90.74**

In the second experiment we wanted to see how the proposed features preform when considering more than two cameras, we obtained 150 images from 3 different models (S100, S110, and S200) of Canon Powershot camera. The images were acquired randomly from the Internet and consist of different sceneries. These 3 models have the same resolution of 2 Megapixels and the images from them have the same size of 1600×1200 (same as the previous 2 cameras studied). However the exact setting used at the time of capture was not known to us. The proposed statistics were collected for the images obtained from the 3 new cameras, and then a multi-class SVM was used to classify data from all of the 5 different camera models, with the same design and testing stages discussed previously. The average accuracy was 88.02%, the corresponding confusion matrix could be seen in table 3. However, we should note that the size and texture diversity of data set being used in the case of 5 cameras, need to be improved for more accurate performance results.

Table 3. The confusion matrix for 5 camera identification case.

		Predicted				
		Nikon	Sony	Canon (S110)	Canon (S100)	Canon (S200)
Actual	Nikon	**89.67**	0.22	4.77	1.64	3.7
	Sony	3.56	**95.24**	0.31	0.34	0.53
	S110	7.85	0.6	**78.71**	4.78	8.04
	S100	3.14	0.32	3.57	**92.84**	0.11
	S200	5.96	2.27	7.88	0.23	**83.63**

5. CONCLUSION AND FUTURE WORK

In this paper we examined the problem of identifying the source camera of a digital image. Although the problem stated in its full generality is difficult, we looked at a simplified version of the problem where we would like to distinguish between images from a limited number of camera models. As one possible solution we proposed a number of features which could be used in classifying a digital image as originating from a set of digital cameras. A classifier based on these features was then used to see how well the measures could classify the images originating from two cameras used in our experiments. We were also able to achieve acceptable accuracy results after the images were re-compressed.

We also showed experimental results with 5 different camera models. Although initial results were encouraging, the true value and performance of the proposed feature set in identifying the camera model would be known when a larger image data set is used. Such a data set needs to be large enough so that the images available from each camera model cover a large range of texture and scenery. Another important research direction is to improve the proposed features which in turn could increase our classification accuracy.

6. REFERENCES

[1] Z. J. Geradts, J. Bijhold, M. Kieft, K. Kurosawa, K. Kuroki, and N. Saitoh, "Methods for identification of images acquired with digital cameras," *Proc. SPIE Vol. 4232, p. 505-512, Enabling Technologies for Law Enforcement and Security*, 2001.

[2] J. Adams, K. Parulski, and K. Spaulding, "Color processing in digital cameras," *Micro, IEEE*, vol. 18, pp. 20–30, Nov.-Dec 1998.

[3] H. Farid and S. Lyu, "Detecting hidden messages using higher-order statistics and support vector machines," *5th International Workshop on Information Hiding.*, 2002.

[4] I. Avcibas, B. Sankur, and K. Sayood, "Statistical evaluation of image quality metrics," *Journal of Electronic Imaging*, April 2002.

[5] I. Avcibas, N. Memon, and B. sankur, "Steganalysis using image quality metrics." *IEEE transactions on Image Processing*, January 2003.

[6] C.-C. Chang and C.-J. Lin, *LIBSVM: a library for support vector machines*, 2001, software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.