Source Camera Identification in Real Practice: a Preliminary Experimentation

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***Abstract*—In this paper, we present an experimental evaluation of one of the most effective source camera identification technique proposed so far, the technique by Lukáš *et al.*. This method uses the characteristic noise left by the sensor on a digital picture as a fingerprint in order to identify the source camera used to take that picture. The goal of our experimentation is to assess the effectiveness of this technique when used with pictures that were previously modified using several common image-processing functions coming with photo-editing tools. Our results seem to confirm that, in most cases, the method by Lukáš *et al.* is resilient to the modifications introduced by the considered image-processing functions. However, we were able to pinpoint some cases where the quality of the identification process deteriorated because of the noise introduced by the pre-processing.**

***Index Terms*—Image Forensics; PRNU; Digital Forensics; Digital Camera Identification; Digital Camera Model Identification; Digital Investigations.**

I. Introduction

In the digital era, the creation and the modification of images (as well as videos) can be performed at a very low cost with simple editing tools which are widely and easily accessible to everyone. As a consequence, it is not possible to always consider authentic an image or a video. This simple fact may become an issue if an image or a video is a digital evidence involved in a Law investigation.

The Image Forensics discipline tries to help the investigators when in presence of digital photographic evidence. One of the many questions that the Image Forensics tries to respond is the *source camera identification problem*, i.e., establish if a given image has been taken from a given digital camera. Many identification techniques have been proposed so far in literature. All these techniques generally work by using the sensor noise left by a digital sensor when taking a picture as a fingerprint for identifying that sensor. These works are generally accompanied with experiments proving the effectiveness of these techniques, both in terms of False Acceptance Rate (FAR) and False Rejection Rate (FRR). Unfortunately, most of these contributions do not take into consideration that, in the real practice, the images that are shared and exchanged through the Internet have often been pre-processed. Instead, it is a common practice to assume, in these experimentations, that the images to be examined are unmodified or, at most, to ignore the effects of the pre-processing.

Even without considering the case of malicious users that could intentionally process a picture in order to fool the existing identification techniques, this assumption is unrealistic for at least two reasons. The first is that, as we were saying before, almost all existing photo-managing software offer several functions for adjusting, sometimes in a "magic" way (see the "I'm feeling lucky" function on Google Picasa [1]), several characteristics of a picture. The second reason is in the way the images are managed by some of the most important social networks and image publishing sites. These services usually make some modifications to the original photos before publishing them in order to improve their appearance or to reduce their size. The contribution of this paper represents a preliminary work to try to figure out how one of the most prominent source camera identification technique responds when in presence of pre-processed images.

A. Organization of the Paper

In Section II we will provide some basic definitions about the source camera identification problem and we will briefly review the existing literature on this topic. In Section III we will introduce in the details the identification technique presented by Lukáš *et al.* in [2] and based on the Photo-Response Non-Uniformity (PRNU) of both CCD [3] and CMOS sensors [4]. In Section IV we present the results of an experimentation of this technique performed on a test-bed of nearly 1500 images taken from 8 different cameras. In our experiments, we compared the performance of this technique when applied to the identification of the cameras used to take both modified and unmodified pictures. Finally, in Section V we sketch some concluding remarks.

II. Digital Camera Identification

Each digital picture contains a random component of noise and a deterministic component, the *pattern noise*, that depends on the sensor used to shoot the picture. The pattern noise is very similar within all the pictures taken by the same sensor.

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The problem of digital camera identification concerns with the identification of the camera that has been used to generate a digital picture, by examining the pattern noise existing in that picture. Such a technique is called *source camera identification* and has not be confused with the more general *digital camera model identification* problem, in which we are just interested in establishing which camera model has been used to take a certain picture.

Up to now, three are the main approaches proposed in literature for the source camera identification problem. These approaches differ in the type of pattern noise that is used.

The first approach uses the *Photo-Response Non-Uniformity* (PRNU) noise, i.e., the noise produced by the sensor due to the inhomogeneity of the silicon wafers used to build it. Lukáš *et al.* [2] and Chen *et al.* [5] proposed two methods for identifying source camera based on the PRNU. These techniques can be used to isolate and extract this noise from a set of pictures taken with a same camera, and use this noise to match or not the cameras with the photos under investigation. Their results show that these methods have high detection rates. Goljan *et al* in [6] used a refinement of the method of Chen to run a digital camera identification experiment on a massive database of digital pictures downloaded from the Internet.

The second approach uses the lens radial distortion that causes straight lines to appear as curved lines on the output images. Choi *et al.* have tried this method in [7]. As a result, they discovered that this method failed to measure the radial distortion except when there are explicit straight lines in the picture to be processed.

The last approach relies on the CFA (*Color Filter Array*) interpolation, which is a technique used by digital cameras after a picture has been taken in order to determine the colors of the scene. This technique produces small non-uniform color zones that can be seen as a noise source. Each camera has its interpolation algorithms and each algorithm produces a small degree of noise that, generally, slightly changes from camera to camera. Bayram *et al.* in [8] explored the CFA interpolation process to determine the correlation structure present in each color band which can be used for image classification. In this direction, Kharrazi *et al.* in [9] and Long and Huang in [10] proposed two methods. The first method identifies a set of image features that can be used to uniquely classify a camera model. The accuracy of this method decreases as the number of cameras increases. The second method obtains a coefficient matrix from a quadratic pixel correlation model where spatially periodic inter-pixel correlation follows a quadratic form. The experimental result seems to suggest that these two methods work better for the camera model identification problem rather than for the source camera identification problem.

III. The Approach by Lukáš *et al.*

We focus our attention on the approach proposed by Lukáš *et al.* because is one of the most effective method, and is not as expensive in terms of hardware resources as other similar methods such as the one proposed by Goljan in [6].

The approach by Lukáš *et al.* works in two stages. In the first stage, the PRNU associated with a CCD sensor is determined by analyzing a batch of images taken with that sensor. In the second stage, given a picture, the procedure evaluates the correlation between the noise existing in that picture and the pattern noise evaluated in the previous stage in order to discern if such a picture has been taken using that CCD sensor.

The extraction of the PRNU from an image is performed by denoising the image using a wavelet-based algorithm. The denoised image is subtracted by the original image giving as output a new image containing several components: the CCD sensor noise, the random noise and various contributions from image signal. Hence, to eliminate the random component of the noise, the denoising procedure is applied to a set of images (captured by the same camera) and the corresponding noise residues are averaged to obtain the reference pattern of a given digital camera.

Afterwards, to determine whether a given image is captured by a digital camera, the noise pattern extracted from the given image is correlated with the reference pattern of the camera. If the correlation value exceeds a pre-determined threshold, then the image was taken with that camera. To estimate the accuracy of the method and to compute the thresholds, they used the Neyman-Pearson criterion, specifying a bound on the FAR.

A. Our Implementation

We implemented the method proposed by Lukáš *et al.* using the Matlab software [11]. We decided to use this software because of its efficiency and because it provides several pre-implemented components (e.g. wavelets functions) which are useful in the implementation of the various identification techniques.

Concerning the implementation, the main ingredient of the method proposed by Lukáš *et al.* is the PNRU filter. This filter simulates the behavior of the Wiener filter in the wavelet domain and it has been suggested in [12]. The Wiener filter is based on a statistical approach and aims to filter the noise of an image.

There exist several families of wavelets, each one suitable for different application and differing in the number of coefficients they use. In early stages of our experiments, we tried several combinations and find out that the optimal choice was represented by 4-levels and 8-levels Daubechies wavelets.

IV. Experimental Analysis

We organized our experiments in three phases. In the first phase, we were interested in assessing the effectiveness of the method by Lukáš *et al.* when applied to the camera identification for unmodified digital pictures. In the second phase, we first pre-processed the original set of pictures using several types of image-processing functions and then repeated the identification process using the decision thresholds determined during the first experiment according to non pre-processed images. In the third phase, we repeated the previous experiments with pre-processed images using, this time, decision thresholds that have been generated starting from pre-processed images. In all experiments we considered seven different camera models, resulting in eight cameras (as shown in Table I). In order to stress the identification method and to cover a wider range of hardware, we choose cameras belonging to different market sectors and different manufactures. Looking at Table I, cameras with ID 1 and 2 have been chosen because they have the same image sensor size and because we believe that they have the same CMOS sensor [13]. Cameras with ID 3 and 4 share the same brand and model. The other four cameras are a mix of common cameras.

TABLE I
CAMERAS USED IN OUR EXPERIMENTATIONS

ID	Model	Sensor type	Image size
1	Canon EOS 400D	CMOS	3888x2592
2	Canon EOS 1000D	CMOS	3888x2592
3	Canon PowerShot A400 instance A	CCD	2048x1536
4	Canon PowerShot A400 instance B	CCD	2048x1536
5	Panasonic Lumix DMC-FZ20	CCD	2048x1536
6	Panasonic Lumix DMC-FS5	CCD	3648x2736
7	Kodak EasyShare CX 7530	CCD	2560x1920
8	HP PhotoSmart E327	CCD	2560x1920

For each camera model $c \in C = \{1, 2, \ldots, 8\}$ we collected two set of images: the *Images for Reference Pattern* (IRP) and the *Images for Testing* (IT). We denote with IRP_c / IT_c the IRP / IT sets for the camera c. The IRP_c set is composed of 128 images collected by taking pictures of a uniform white surface. The images have been taken on a tripod, with no flash, auto-focus, no-zoom, best JPEG compression quality, and with all the other options set to their default values. The IT_c set is made of 64 images portraying different types of subjects. In this case, the images have been taken using different types of settings, with the exception of the JPEG compression quality and of the image size, both always set to maximum.

The effectiveness of the identification has been measured by counting the number of pictures erroneously rejected by the identification technique over the total number of pictures taken with a certain camera (FRR). Moreover, in all our experiments we have set our decision thresholds in such a way to keep to 0 the total number of pictures erroneously classified as taken with a certain camera (FAR). All the experiments have been run on a server equipped with two 4-core Intel Xeon X7350 processors at 2.93GHz and using the Linux Ubuntu O.S.

A. Experiment 1

A preliminary problem to be faced when applying the method by Lukáš *et al.* is to ensure that the two images to be correlated (i.e., the image reference pattern and the image to be identified) must have the same size. This condition can be easily met in three different ways:

- **Sub**: extract from both images two subimages of the same size (e.g., extract two images originating at point $(0, 0)$ and having size 512x512);
- **Crop**: crop the larger image to match the smaller image;
- **Resize**: resize the larger image to match the smaller image;

The original method proposed by Lukáš *et al.* uses the **Crop** approach. In our case, we decided to test also the other two approaches in order to determine which one performs better. According to our experiments, presented in Table II, the best approach seems to be **Resize** while the worst is **Sub**. The reason for such a bad performance is likely to reside in the elimination of a large part of the original image, performed by this technique when processing large pictures. The average resolution of the pictures used in our experiments is near 2560x1920. As a consequence of this, the cropped image, whose size is fixed to 512x512, retains only the 5% of the original image and of its signature, and thus is subject to a worst correlation. In all the remaining experiments presented in this paper, we will always use, when needed, the **Resize** technique.

Figure 1 presents the scatter plot of the correlations between all the images of the data set and the reference pattern of the Canon PowerShot A400 instance A.

B. Experiment 2

The second experiment was intended to test the resiliency of the method by Lukáš *et al.* when used for classifying pictures that have been subject to some sort of pre-processing. The experiment has been organized by first applying six different commonly-used image processing operators to the data set D_{IT} used in the previous experiment. Then, we applied the identification method on the resulting data sets using, for each camera, the same reference pattern and decision threshold determined in the previous experiment. Finally, we compared the outcoming classification with the result of the classification on the original (i.e., not pre-processed) pictures. The operators that we considered in our experiments, as implemented by the Adobe Photoshop software [14], are:

- **Auto Level Adjustment** (*ALA*): this function automatically corrects the highlights and shadows in a picture and adjusts the tones so that lowest level in the picture is completely black and the brightest white is full white. Auto Levels tunes each color channel individually, and this may remove or introduce color casts;
- **Auto Contrast** (*ACS*): this function adjusts the overall contrast and mixture of colors within an image, without introducing or removing color casts, and permits to create a more accurate tonal and color-correction;
- **Auto Color** (*ACO*): this function adjusts contrast and color of an image by neutralizing the midtones and clipping the white and black pixels;
- **Resizing** (*R75*, *R50*, *R25*): this operator rescales the image to match a smaller size; the interpolation algorithm

TABLE II
DECISION THRESHOLDS, FRR AND NUMBER OF IMAGES REJECTED ON THE RED CHANNEL FOR THE EXPERIMENTS SUB, CROP AND RESIZE.

	Sub		**Crop**		**Resize**	
ID	Decision threshold	Images rejected (FRR)	Decision threshold	Images rejected (FRR)	Decision threshold	Images rejected (FRR)
1	0,0120	—	0,0095	—	0,0095	—
2	0,0120	2 (0,0313)	0,0122	—	0,0122	—
3	0,0216	5 (0,0781)	0,0188	3 (0,0469)	0,0188	3 (0,0469)
4	0,0243	2 (0,0313)	0,0333	—	0,0333	—
5	0,0705	—	0,0826	—	0,0826	—
6	0,0222	2 (0,0313)	0,0187	—	0,0187	—
7	0,0124	62 (0,9688)	0,0026	38 (0,5938)	0,0061	—
8	0,0420	—	0,0226	—	0,0226	—
total number of images rejected		73		41		3

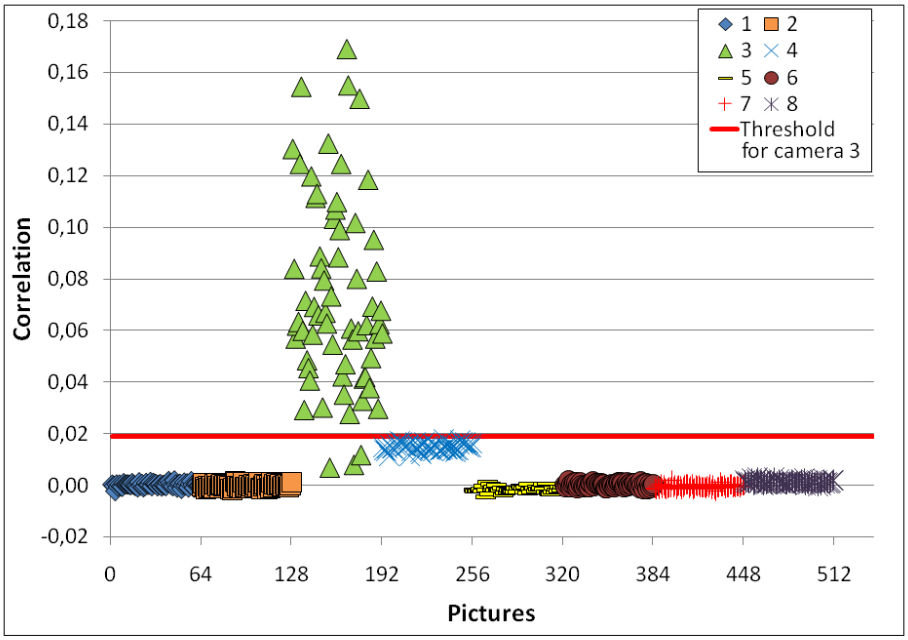

Fig. 1. Scatter plot of the correlations between all the images of the data set and the Image Reference Pattern of the camera with ID 3.

is the bicubic which produces noticeably sharper images than other methods such as bilinear or nearest neighbour, and it is a good balance between processing time and output quality. We processed images with this operator by changing the scale factor. We obtained pictures with the image size of 75%, 50% and 25% of its original sizes.

TABLE III
NUMBER OF IMAGES REJECTED ON MANIPULATING PICTURES WITH THRESHOLDS COMPUTED IN EXPERIMENT 1 - RESIZE

	Operator						
ID	**No OP**	**ALA**	**ACS**	**ACO**	**R75**	**R50**	**R25**
1	—	—	—	—	—	—	—
2	—	4	4	4	2	3	10
3	3	4	4	4	4	6	34
4	—	2	2	2	2	2	1
5	—	1	1	1	14	54	64
6	—	1	1	1	3	3	25
7	—	1	1	1	—	—	—
8	—	2	2	2	2	2	32
total	3	15	15	15	27	70	166

The results of these experiments, presented in Table III, are noteworthy. We observe a small increase in the number of erroneously rejected images, when considering pictures processed with the ALA, ACS and ACO operators. This increase is much more significant when turning to resized images. Here, the number of rejected images is high and grows linearly with the resize factor. By examining in details these results, we notice that there are some camera models where the identification method performs very bad when used with resized images. It is the case of models 3,6,8, and, especially, model 5. This seems to suggest either that the resize operator may have a very strong influence on the correlation between the picture and the reference pattern noise, and that this influence may greatly vary according to the camera being used, even for different cameras of the same model. Moreover, we observe that if the decision thresholds are chosen using, as a reference, pictures that have not been previously pre-processed, the identification method may be at risk.

TABLE IV
DECISION THRESHOLDS, FRR AND NUMBER OF IMAGES REJECTED ON THE RED CHANNEL FOR THE EXPERIMENTS ALA, ACS AND ACO.

	ALA		**ACS**		**ACO**	
ID	Decision threshold	Images rejected (FRR)	Decision threshold	Images rejected (FRR)	Decision threshold	Images rejected (FRR)
1	0,0098	—	0,0098	—	0,0098	—
2	0,0026	2 (0,0313)	0,0026	2 (0,0313)	0,0027	2 (0,0313)
3	0,0184	4 (0,0625)	0,0195	4 (0,0625)	0,0182	4 (0,0625)
4	0,0180	1 (0,0156)	0,0180	1 (0,0156)	0,0177	1 (0,0156)
5	0,0821	—	0,0817	—	0,0822	—
6	0,0018	1 (0,0156)	0,0018	1 (0,0156)	0,0019	1 (0,0156)
7	0,0058	—	0,0059	—	0,0059	—
8	0,0217	—	0,0219	—	0,0219	—
total number of images rejected		8		8		8

TABLE V
DECISION THRESHOLDS, FRR AND NUMBER OF IMAGES REJECTED ON THE RED CHANNEL FOR THE EXPERIMENTS R75, R50 AND R25.

	R75		**R50**		**R25**	
ID	Decision threshold	Images rejected (FRR)	Decision threshold	Images rejected (FRR)	Decision threshold	Images rejected (FRR)
1	0,0118	—	0,0111	—	0,0100	—
2	0,0026	2 (0,0313)	0,0044	2 (0,0313)	0,0058	2 (0,0313)
3	0,0115	4 (0,0625)	0,0074	4 (0,0625)	0,0088	4 (0,0625)
4	0,0097	1 (0,0156)	0,0061	1 (0,0156)	0,0070	1 (0,0156)
5	0,0588	—	0,0409	—	0,0173	—
6	0,0022	1 (0,0156)	0,0031	1 (0,0156)	0,0052	3 (0,0469)
7	0,0088	—	0,0118	—	0,0135	—
8	0,0214	—	0,0164	—	0,0050	1 (0,0156)
total number of images rejected		8		8		11

C. *Experiment 3*

In our previous experiment we have seen that if we try to classify pre-processed pictures using a classifier that has been tuned for unmodified pictures, the identification method by Lukáš *et al.* may fail, in some cases, with a very high probability. These failures are mostly due to the alteration of the pattern noise existing in a processed picture. This alteration implies a smaller correlation with the reference pattern noise. A natural solution to this problem consist in lowering the decision threshold used during the classification, so to correctly identify also pictures with smaller correlations. The results, documented in Table IV, show a significant improvement on the quality of the classification, with respect to the second experiment. In this case, we have been able to obtain FRR rates which are very similar to those experienced with our first experiment. However, such a result comes at a cost. The new decision thresholds are, in some cases, much lower than the original ones. For example, we had to lower the decision threshold related to camera 5 to more than the 90% of its original value, thus raising the possibility of wrong classifications on larger data sets.

The same behavior can be noted when using the R75, R50, and R25 operators. As shown in Table V, even for these operators, the thresholds change without any correlation with the percentage of resize. In other words, what we should have expected with this experiment is that reducing the image size will decrease the correlation index. In practice this not happens for all the cameras because we notice different behavior for some cameras. In particular, the threshold of the camera with ID 8 goes down while those for camera with ID 7 increase.

Analyzing Figure 2 can be noted that no relation exists between the thresholds and the market sector of the camera models used. Moreover, each camera is independent from other cameras since it presents its own threshold. Indeed, the thresholds differ for the same camera model (cameras 3 and 4) and for camera models probably equipped with the same sensor (cameras 1 and 2). Furthermore, the figure points out how the results of the operators are strictly dependent on the camera, showing that the operators do not linearly affect all the cameras.

V. CONCLUSIONS

In this paper, we evaluated the effectiveness of the source camera identification technique from Lukáš *et al.*, when using, as input, pictures that have altered by means of commonly-used image processing operators. The result of our experiments show, first of all, that the classification of the altered images may perform very bad if the classifier has been tuned using unmodified images (see subsection IV-B). This problem can be fixed by tuning the classifier according to a data set of altered images and, consequently, by lowering the decision thresholds used to establish if a picture has been taken with a given camera. In this new configuration, the Lukáš method confirms its effectiveness (see subsection IV-C), even when processing altered images, although there are processing operators, like resizing and/or increasing the compression factor of a jpeg picture, which seems to have a bad effect on the results of the classification.

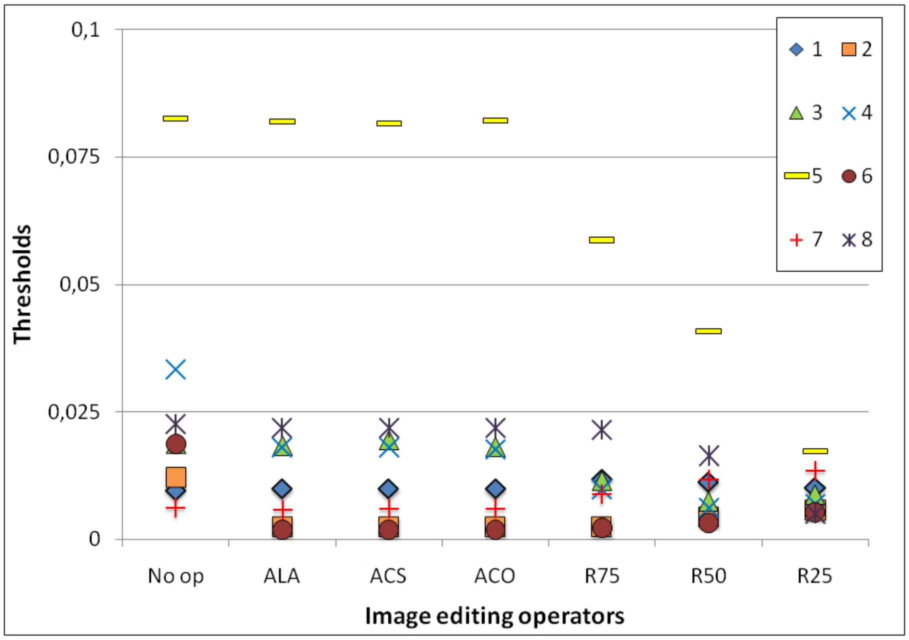

Fig. 2. Thresholds values used according to the pre-processing operators being tested.

As a side effect of our experimentation, we experienced that the usage of an operator of type *Resize* seems to be preferable to an operator of type *Crop* when calculating the correlation between two images of different sizes.

The drop of the threshold involves, nonetheless, some problems while choosing which threshold to use during a real investigation on a photographic exhibit. In fact, if the threshold computation would have been performed on a set of images "unaltered", then the obtained threshold value could have been greater than the correlation index of a given, altered, image under scrutiny. Otherwise, if the computation of the decision threshold would be computed on a set of images altered, then in such a case the FRR would be increased.

We intend to proceed with our research by increasing the number of cameras and pictures involved in our experiments, by implementing some other classification techniques and, finally, by extending our experimentations to pictures that have been previously published and processed, and then downloaded, from social networks and photo publishing sites such as Facebook and PicasaWeb.

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