IMPROVEMENTS ON SENSOR NOISE BASED SOURCE CAMERA IDENTIFICATION

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ABSTRACT

In [1], a novel method for identifying the source camera of a digital image is proposed. The method is based on first extracting imaging sensor's pattern noise from many images and later verifying its presence in a given image through a correlative procedure. In this paper, we investigate the performance of this method in a more realistic setting and provide results concerning its detection performance. To improve the applicability of the method as a forensic tool, we propose an enhancement over it by also verifying that class properties of the image in question are in agreement with those of the camera. For this purpose, we identify and compare characteristics due to demosaicing operation. Our results show that the enhanced method offers a significant improvement in the performance.

Index Terms— Image Forensics, Source Digital Camera Identification, Pattern Noise, Demosaicing Artifacts

1. INTRODUCTION

Digital imagery is becoming an integral part of our daily lives at a rapid pace. As a result of this shift in technology, conventional film photography is disappearing. When combined with the availability of extremely powerful image processing techniques and computer graphics technologies, this trend poses new issues and challenges concerning the authenticity and integrity of digital images. This problem is further exacerbated when photographic evidence is considered. Digital image forensics techniques aim at closing this gap by uncovering facts about a digital image. Due to wide popularity of digital cameras, design of many digital image forensics techniques requires an understanding of the fundamental operation of the digital camera.

In this regard, the core element of a digital camera is the imaging sensor which measures the intensity of light incident on it. An imaging sensor is essentially a two-dimensional array of light sensitive elements called pixels based on CCD or CMOS technology. Similar to other electronic devices, an imaging sensor is also subject to measurement noise [1]. More specifically, the noise in a digital image can be assumed to have two main components: (1) shot noise, a random component, and (2) pattern noise, a deterministic component. Furthermore, the pattern noise consists of two main components which are the fixed pattern noise (FPN) and the photo-response non-uniformity noise (PRNU).

Main component of the fixed pattern noise (FPN) is due to dark currents which refers to pixel-to-pixel differences when the sensor array is not exposed to light. Dark current noise can be easily compensated within a camera by taking a dark frame and subtracting it from a sensor output. On the other hand, the other part of the pattern noise, photo-response non-uniformity noise (PRNU), is primarily caused by sensitivity of pixels to light and it is primarily caused by the imperfections in the sensor manufacturing process. However, unlike dark currents PRNU cannot be easily corrected by subtraction and requires an operation called *flat-fielding*. Due to inability realize flat-fielding within a digital camera, photo-response non-uniformity noise makes it a compelling means for characterizing digital cameras.

In [1], authors proposed a method to extract the pixel non-uniformity noise associated with a CCD sensor. The key idea of the method is to denoise the image by a wavelet-based denoising algorithm so that the resulting residue contains the needed noise components. However, since the underlying image model used in denoising is an idealistic one the residue signal also contains contributions from the image signal. Hence, to eliminate random component of the noise denoising 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. Later, to determine whether a given image is captured by a digital camera, the noise pattern extracted from the individual image is correlated with the reference pattern of the digital camera. A decision is made based by comparing the measured correlation statistic to a pre-determined decision threshold. Figure 1 illustrates the steps involved in matching an image to a digital camera.

On the other hand, since each sensor element (pixel) is essentially monochromatic, capturing color images requires separate CCD arrays for each color component. However, due

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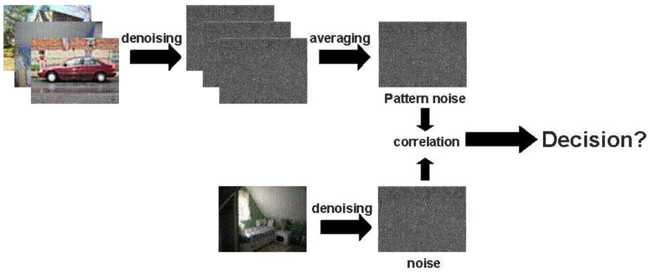

Fig. 1. Illustration of the Sensor Pattern Noise Based Source Identification Method Proposed in [1]

to cost considerations most digital cameras use only a single sensor along with an array of spectral filters in front of the sensor, namely, color filter array (CFA). The CFA essentially arranges pixels in a pattern so that each pixel captures one of the red, green or blue colors, and the missing color values for each pixel is later computed through a process called demosaicing, a form of interpolation that uses color information from neighboring pixels to obtain the color value of a pixel. At the same time, however, demosaicing operation (interpolation) introduces pixel-wise correlations whose specific form depends on the specifics of the interpolation. In [2, 3], we utilize such artifacts to identify the source camera-model of a digital image. Since, extraction of a reference pattern noise of a digital camera requires the availability of a number of images (taken by the same camera), this approach can be incorporated to sensor noise based source camera identification by also characterizing the underlying demosaicing operation and verifying that the test image also exhibits similar characteristics. Such a combined test will improve the accuracy in the matching process since in addition to individual camera properties camera's class properties are also involved in the decision.

The rest of the paper is organized as follows: In Section 2, we discuss the limitations of the methodology described in [1] to be applied in a forensic investigation and present performance results obtained under a more realistic scenario. In Section 3, the potential of demosaicing artifacts [2, 3] in identifying the class properties of camera (e.g., camera-model) from a given set of images is discussed and experimental results are presented. Incorporation of the demosaicing artifacts to sensor noise based source camera identification method and the corresponding performance results are given in Section 4. Our conclusions and future efforts are given in Section 5.

2. PATTERN NOISE AND SOURCE CAMERA IDENTIFICATION

In [1], the authors carry out the performance analysis (e.g., detection and false-positive rates) by considering pairwise comparisons since the corresponding (pairwise) distributions can be well modeled by the generalized Gaussian. However, when the test data is constructed by pooling all images taken by other digital cameras together the distribution no longer follows the model. Obviously, this approach is not preferable when real-life forensics analysis is considered as it does not yield to true false-positive (false-acceptance) rates, which is one of the most important parameters of a forensics method. Therefore, in our setup, we rather compared the correlation values obtained from images taken by a given camera with the correlation values calculated from a mixed set of images. (It should also be noted that in our experimental setup there is no overlap between the training and test image sets.) The performance results obtained under this setting are given in Figure 2. It can be observed that the overall performance of the method is found to be worse than the reported results in [1] due to differences in the experiments. However, in the next section, we describe a mechanism to improve the false-positive versus true-positive detection performance of the sensor noise based source camera identification technique.

In our experiments, we considered three different digital cameras. These cameras include a Sony DSC 90, a Sony DSC 72P and a Canon Powershot S1 IS. Number of images taken by these three cameras are 1214, 894 and 944, respectively. The images in all sets are in JPEG format and are of sizes 1728×2304, 960×1280, and 1536×2048, respectively. In each set, 300 images are selected randomly (as the training set) and used in extraction of the reference pattern of each camera. The rest of the images are used for testing and verification purposes.

In order to extract the noise patterns, we implemented the very same denoising filter employed in [1]. (It must be noted that the authors recently proposed enhancements over this method as described in [4].) The performance results for the three cameras are obtained in the following manner:

- The reference patterns are obtained by averaging the 300 noise residual signals from the training sets of each camera.
- Denoising algorithm is applied to each of the test images and the extracted noise is correlated with the reference pattern. It should be noted that 300 training images are not used in this step.
- Denoising algorithm is applied to a set of approximately $80,000$ images. Noise residuals extracted from these images are also correlated with the sensor pattern noise of each camera. In cases when the size of the noise image is different from the size of the sensor noise pattern, the larger one is cropped appropriately to match the smaller one.

As a result of the last two steps, we obtain two set of correlation values for each camera. The distribution of two detection statistics are then used to obtain the receiver operating characteristic (ROC) curves in terms of false rejection rate (FRR) and false acceptance rate (FRR) values, as given in Figure 2.

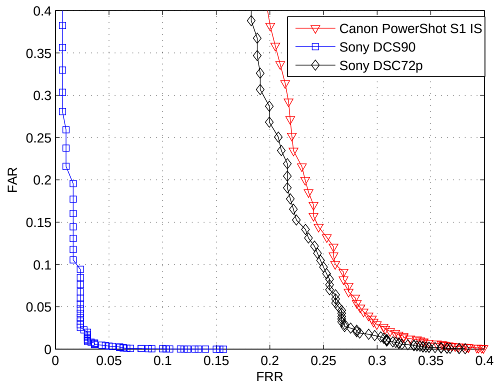

Fig. 2. ROC curves for sensor pattern noise based method

It can be observed from these performance results that, although one of the three digital cameras can be identified more successfully than the others, the measured FAR and FRR values are not satisfactory enough for the method to be regarded as as a reliable forensic tool.

It should be emphasized that if the test images also include the training set (i.e., the 300 images), the correlation values would yield a better differentiation between the test images and the randomly generated image data set. Figure 3 shows the improvement in the correlation values when the reference pattern noise extracted from a camera is correlated with the noise extracted from images in training set as compared to images in the test set. While the mean value of the correlations obtained from the set of test images is 0.08, the mean calculated over the set of training images is 0.12.

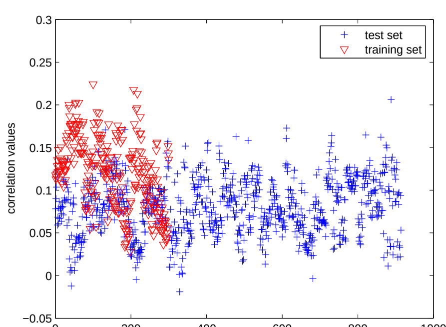

Fig. 3. Distribution of the correlation values obtained from test and training datasets for Sony DSC S90

3. DETECTING INTERPOLATION ARTIFACTS

In [2, 3], we proposed a source camera-model identification method based on the observation that interpolation operation will introduce artifacts in the form of periodic correlations among image pixels [5]. The specific form of the the artifacts depend on the specifics of the demosaicing algorithm and they can be used to classify the images as originating from a certain class of digital cameras. In this paper, we reduce the problem to a single-class classification problem to decide whether or not an image is taken by a particular digital camera model. In other words, rather than trying to categorize the structure of artifacts, we determine if the artifacts exhibit a specific structure. Since in the feature space, features associated with all digital cameras will be more dispersed as compared to those of a single camera, the difficulty of classification will be lower thereby yielding an improvement in the performance.

In our experiments we deployed the images taken by three cameras as in Section 2 and extracted the features from the image set (e.g., 600 images for each camera). In a similar manner, we extracted features from a mixed set of 5300 images captured by various models of digital cameras. In the first step of our experiments, we used a one-class SVM classifier to decide whether or not an image is taken by a Sony DSC S90 camera. For this, we used 300 images, out of 600 images, to train the classifier. Then, we tested the constructed classifier on remaining 300 images and the images from the mixed set. The resulting accuracy is computed as 83.5%. To overcome the limitations of one-class classifier design (in obtaining the decision hyper-plane), in the second set of our experiments, we considered two-class classification. Hence, in addition to 300 images from the camera training set we included 300 images from the mixed set in designing the classifier, where the remaining $300 + 5000$ images are used for the testing the resulting classifier. In this case, the performance increased to 98.16%. Since the performance is better in this case, we designed two-class classifiers also for camera Sony DSC P72 and Canon Powershot S1 IS. The corresponding ROC for these there cameras are shown in Figure 4.

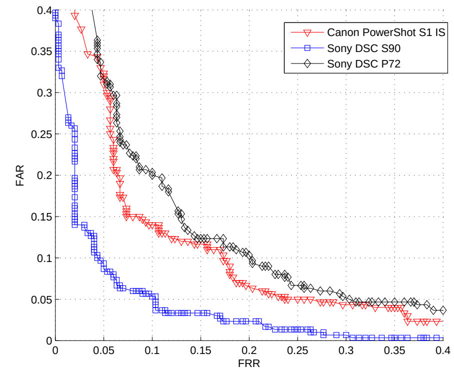

Fig. 4. ROC curves for demosaicing artifacts based method

These results show that demosaicing artifacts give better results when used with single-class approach. In the next section we show how to use this approach to reduce false-

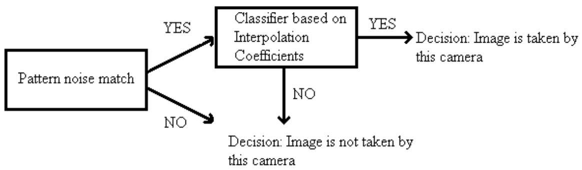

Fig. 5. The proposed combined decision process

acceptance rate of the sensor noise based source camera identification method.

4. COMBINING PATTERN NOISE PROPERTIES WITH DEMOSAICING CHARACTERISTICS

To improve the accuracy of sensor noise based source camera identification technique described in Section 2 we enhance it by also verifying the consistency of demosaicing artifacts, as described in Section 3.

The two methods are used in sequence before making a decision, see Figure 5. In the first round, match of sensor noise is checked and then, if the result is positive, secondary features are analyzed. Therefore in the experiments, at first positive decisions due to pattern noise matching are determined. Then, these images are feed to the classifier to verify the consistency of demosaicing artifacts. Hence, the final decision is made by the classifier.

It should be noted that in this setting the use of a classifier may eliminate some of the false positives while at the same time reducing some of the true detections as well. Therefore, the question to be answered is if the decrease in false-positive rate can compensate for the decrease in the true detection rate. The results corresponding to the sensor pattern noise based method and the proposed combined decision process are given in Figure 6. Here, the combined approach is compared to sensor noise based detection in terms of its accuracy which is defined as the ratio of the number of correct decisions to overall number of decisions. For example, when the decision threshold value for sensor pattern noise based detection scheme is set to 0.01, classifier improves the accuracy of the correct detection rate from 72.58% to 93.41% for Sony DSC 72P.

Our results show that cascaded decision process offers viable alternative as the false-positive rate decreases considerably whereas the reduction in true detection rate is rather low. It can be seen that for all cameras and at all considered thresholds, the accuracy of the method is above 90%.

5. CONCLUSION AND FUTURE WORK

In this paper, we propose an improvement over source camera identification based on sensor's pattern noise. Our method is motivated by the observation that when the reference pattern of a digital camera is correlated by the noise extracted from many images, as initially proposed in [1], the resulting false positives are more than estimated by the numerical computations. To address this problem, we propose a scheme that enables application of this method in a more realistic forensics scenario. This is realized by incorporating the digital camera's demosaicing characteristics into the decision process thereby increasing the reliability of the decision. Preliminary results show that we are able to reduce false-acceptance rate of the sensor pattern noise method. Our future work will focus on generalization of these results over a large set of digital cameras.

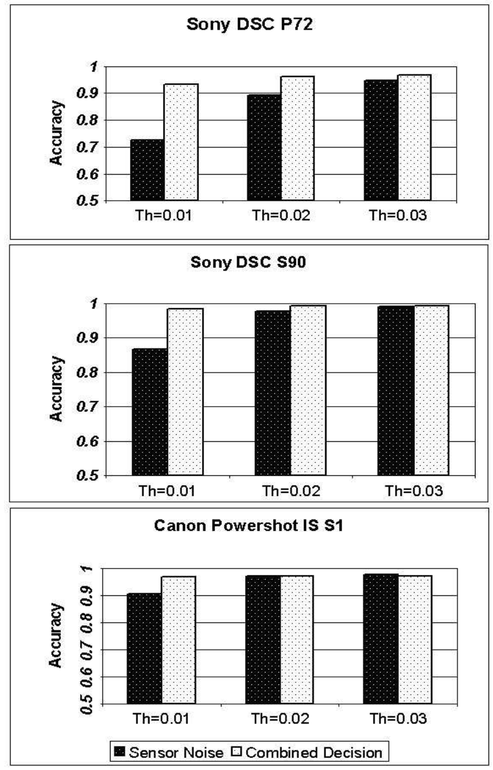

Fig. 6. Performance comparison for three different cameras

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