Forensic Camera Classification: Verification of Sensor Pattern Noise Approach

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Abstract

Digital images can be obtained through a variety of sources including digital cameras and scanners. In many cases the ability to determine the source of a digital image is important. This paper verifies the method presented in (Lukas et al. 2005) for authenticating images that have been acquired using digital still cameras. The method is based on the usage of imaging sensor pattern noise. A reference pattern is estimated for each camera and is treated as a unique fingerprint of that camera. To identify the source camera of an unknown image, the noise extracted from the image is correlated with all the reference camera patterns obtained from training images. This correlation based approach is shown to have close to 100% classification accuracy.

1. Introduction

Advances in digital imaging technologies have led to the development of low-cost and high-resolution digital cameras and scanners, both of which are becoming ubiquitous. Digital images generated by various sources are widely used in a number of applications from medical imaging and law enforcement to banking and daily consumer use. Along with the proliferation of digital content, the functionality of image editing software is also escalating, allowing even an amateur to easily manipulate digital images. Under these circumstances digital images can be used as "legal" only if they can be properly authenticated. Forensic tools that help establish the origin, authenticity, and the chain of custody of such digital images are essential to a forensic examiner. Therefore, a reliable and objective way to examine digital image authenticity is needed.

There are various levels at which the image source identification problem can be addressed. One may want to find the particular device (digital camera or scanner) which generated the image or one might be interested in knowing only the make and model of the device. A number of robust methods have been proposed for source camera identification (Bayram et al. 2005; Farid and Popescu 2005; Geradts et al. 2001; Kharrazi et al. 2004; Lukas et al. 2005; Lukas et al. 2005; Lukas et al. 2006). In (Khanna et al. 2007), a novel technique for classification of images based on their sources, scanned and non-scanned is presented.

One approach for digital camera identification is based on characterization of the imaging sensor used in the device. In (Geradts et al. 2001), it is shown that defective pixels can be used for reliable camera identification even from lossy compressed images. This type of noise, generated by hot or dead pixels, is typically more prevalent in cheap cameras and can be visualized by averaging multiple images from the same camera. These errors can remain visible even after the image is compressed. However, many cameras post-process the captured image to remove these types of noise, so this technique cannot always be used.

Lukas et al. did the pioneering work in developing source camera identification techniques using the imaging sensor's pattern noise (Lukas et al. 2005; Lukas et al. 2005; Lukas et al. 2006). The identification is based on pixel nonuniformity noise which is a unique characteristic of both CCD (charged coupled device) and CMOS (complementary metal oxide semiconductor) sensors. Reliable identification is possible even from images that are resampled and JPEG compressed. Pattern noise is caused by several factors such as pixel nonuniformity, dust specks on the optics, optical interference, and dark current (Holst 1998; Janesick 2001). The high frequency part of the pattern noise is estimated by subtracting a denoised version of the image from the original. This is performed using a wavelet based denoising filter (Mihcak 1999). A camera's reference pattern is determined by averaging the noise patterns from multiple images obtained from the camera. The reference pattern serves as an intrinsic signature of the camera. To identify the source camera, the noise pattern from an image is correlated with the known reference patterns from a set of cameras. The camera corresponding to the reference pattern giving maximum correlation is chosen to be the source camera. This scheme is extended in (Lukas et al. 2006) for detection of forgery in digital camera images. In (Chen et al. 2007; Chen et al. 2008), an improved method for source camera identification based on joint estimation and detection of the camera photoresponse non-uniformity (PRNU) in images is presented. In this paper the methods implemented

are using the simple averaging method as in (Lukas et al. 2005), thus further improvements in results may be obtained by using the improved method for sensor noise estimation presented in (Chen et al. 2007; Chen et al. 2008).

In this paper the results presented in (Lukas et al. 2005) are verified using a different set of cameras. All the experiments are performed without making any contact with the authors of the earlier work.
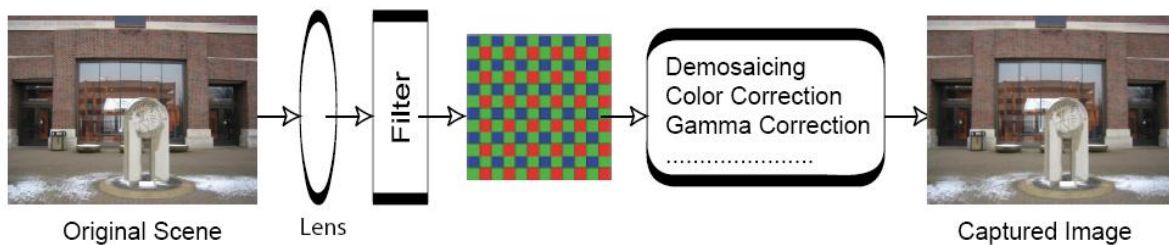
2. Digital Camera Overview

2.1   Imaging Pipeline

Figure 1. Imaging pipeline for a digital camera.

The basic elements of a digital camera imaging pipeline are shown in Figure 1. Even though the exact design details and algorithms differ between manufacturers and models, the basic structure of the digital camera pipeline remains the same.

First, light from a scene enters the camera through a lens and passes through a set of filters including an anti-aliasing filter. Next the light is "captured" by a sensor. These sensors, typically CCD or CMOS imaging sensors, are color blind in the sense that each pixel captures only intensity information from the light hitting it. To capture color information, the light first passes through a color filter array (CFA) which assigns each pixel on the sensor one of three (or four) colors to be sampled. Shown in Figure 2 are CFA patterns using RGB and YMCG color spaces, respectively, for a 4×4 block of pixels. The individual color planes are filled in by interpolation using the sampled pixel values using a number of different interpolation algorithms depending upon the manufacturer.
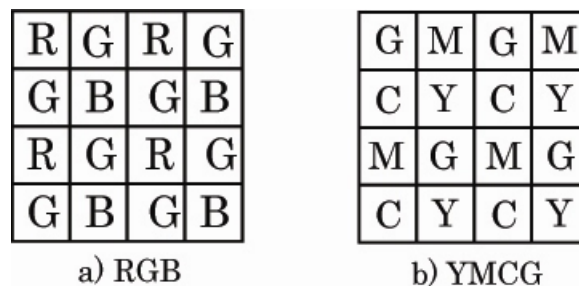

Figure 2. CFA patterns.

Next, a number of operations are performed by the cameras which include white point correction and gamma correction. The image is finally written into the camera memory in a user-specified image format (e.g. RAW, TIFF or JPEG).

Although these operations and stages are standard in a digital camera pipeline, the exact processing details in each stage vary between manufacturers, and even between different camera models from the same manufacturer. This variation from one camera model to another can be used to determine the type of camera used to acquire a specific image.

2.2   Sensor Noise

The manufacturing process of imaging sensors introduces various defects which create noise in the pixel values (Holst 1998; Janesick 2001). These noises can be classified into three classes based on their origins and effects. First is shot noise or random noise which is present in any exposure. Shot noise is not of use in source camera identification because it varies between frames.

The second type of noise is pattern noise which refers to any spatial pattern that does not change significantly from image to image. Major sources of pattern noise are point defects, fixed pattern noise (FPN), and photoresponse nonuniformity (PRNU). Point defects, such as hot or dead pixels, are typically compensated for by the camera during post-processing. FPN is an additive noise caused by stray currents from the sensor substrate into the individual pixels known as dark currents. Dark current is a function of detector size, doping density, foreign matter trapped during fabrication, and is independent of incident light intensity. PRNU is the variation in pixel sensitivity caused by variations between pixels such as detector size, spectral response, thickness in coatings and other imperfections created during the manufacturing process. These variations can be modeled as per-pixel multiplicative factors. Both FPN and PRNU remain the same across multiple frames, but vary across different sensors.

The third type of noise is readout noise which is introduced when reading data from the sensor. It is most visible at high ISO or when the image has been excessively brightened.

While noise is generally thought of as an additive term, as is the case with FPN, PRNU is multiplicative factor. This view of the noise is well established in imaging sensor literature and the same terminology is used in this paper as well. Frame averaging will reduce the noise sources except for FPN and PRNU. Although FPN and PRNU are different, they are collectively known as scene noise, pixel noise, pixel nonuniformity, or simply pattern noise (Holst 1998).

The focus of this paper is on using pattern noise for source camera identification. However, it is extremely difficult to obtain the pattern noise by direct methods such as flat fielding. This is due to the fact that in most general purpose cameras, the raw sensor data is unavailable. Furthermore, a number of non-linear image processing algorithms are applied to transform voltage sensed by the imaging sensor to the final JPEG or TIFF image data. So, in absence of any direct method, indirect methods of estimating the sensor noise are used. In (Lukas et al. 2005) a method of estimating sensor noise is successfully used for source camera identification. This proposed method uses a wavelet filter (Mihcak 1999) in combination with frame averaging to estimate the pattern noise in an image.

3. Correlation Based Approaches

Digital cameras mostly use CCD/CMOS imaging sensors. The imaging sensor's pattern noise has been successfully used for source camera identification as described in (Lukas et al. 2005). The high frequency part of the pattern noise is estimated by subtracting a denoised version of an image from the original image.

As in (Lukas et al. 2005) a wavelet based denoising filter (Mihcak 1999) is used for denoising the image. A camera's reference pattern is determined by averaging the noise patterns from multiple images captured by the camera. This reference pattern serves as an intrinsic signature of the camera (Figure 3). The steps shown in Figure 3 are independently applied to all the cameras in our training dataset and a set of camera reference patterns is obtained. Figure 4 shows the steps involved in source camera identification from an unknown image. First step is to estimate the sensor noise in the test image by using the same denoising filter as used in the training phase. Then this noise pattern is correlated with the camera reference patterns obtained in the training step. Finally, the camera corresponding to reference pattern with the highest correlation is chosen to be the source camera (Lukas et al. 2005).

There have been some recent improvements in the sensor noise based methodology proposed in (Lukas et al. 2005). These improvements show better estimation of camera reference patterns using smaller training sets and improved classification. In (Chen et al. 2007; Chen et al. 2008), an improved method for source camera identification based on joint estimation and detection of the camera photoresponse non-uniformity (PRNU) in images is presented. Post-processing operations applied on the estimated reference patterns reduce the positive correlation between reference patterns from cameras of same make and model and thus further reduce the false alarm rates in distinguishing cameras with same make and model. The methods implemented in the present study use the simple averaging method as in (Lukas et al. 2005), thus further improvements in results, particularly error analysis showing low false alarm rates, may be obtained by using the improved method for sensor noise estimation presented in (Chen et al. 2007; Chen et al. 2008). Another improvement is obtained by replacing correlation with cross-correlation and using peak to correlation energy (PCE) as part of the decision criteria (Goljan and Fridrich 2008). This eliminates the problems with finding experimental thresholds for correlation values and instead uses Neyman-Pearson hypothesis testing for computing the threshold based on a chosen false alarm rate. Source camera identification using sensor noise is extended in (Lukas et al. 2006) for detection of forgery in digital camera images.
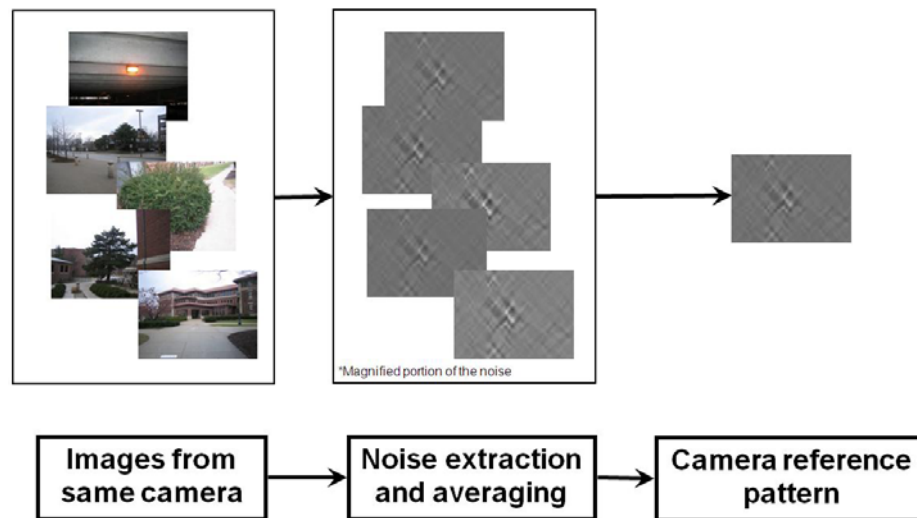

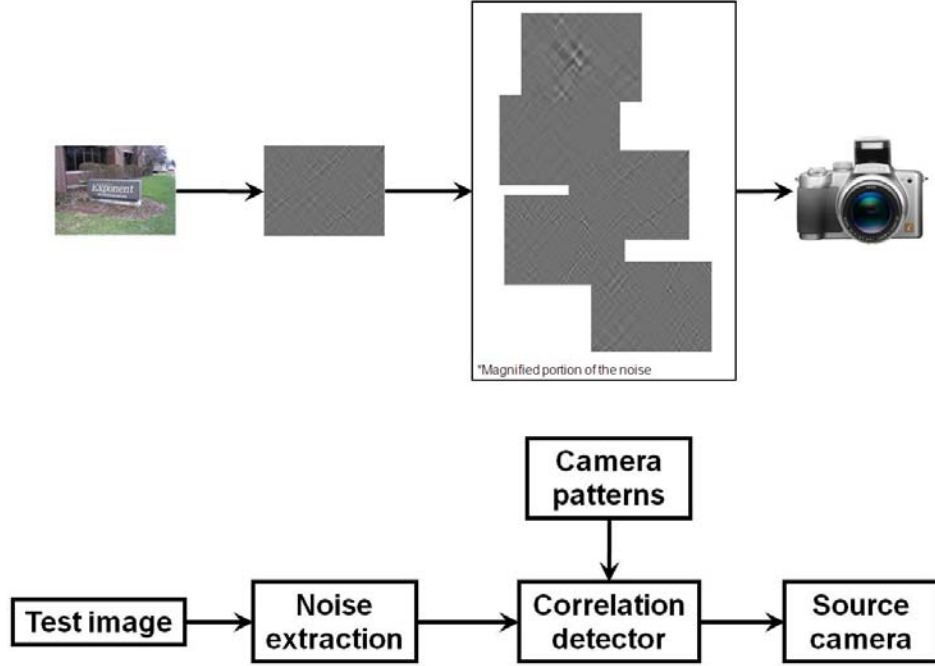Figure 3. Classifier training for correlation-based approach.

*Magnified portion of the noise

Camera patterns → Correlation detector

Test image → Noise extraction → Correlation detector → Source camera

Figure 4. Source scanner identification using a correlation-based detection scheme.

Let I^k denote the kth input image of size M×N pixels (M rows and N columns). Let I^k_{noise} be the noise corresponding to the original input image I^k and let $I^k_{denoised}$ be the result of applying a denoising filter on I. Then as in (Lukas et al. 2005),

$$I^k_{noise} = I^k - I^k_{denoised} \tag{1}$$

Let K be the number of images used to obtain the reference pattern of a particular digital camera. Then the two-dimensional array reference pattern is obtained as

$$\widetilde{I}^{array}_{noise}(i,j) = \frac{1}{K}\sum_{k=1}^{K} I^k_{noise}(i,j); \qquad 1 \le i \le M, 1 \le j \le N \tag{2}$$

Correlation is used as a measure of similarity between the camera reference pattern and the noise pattern of a given image (Lukas et al. 2005). Correlation between two vectors $X,Y \in R^N$ is defined as

$$C(X,Y) = \frac{(X - \bar{X}).(Y - \bar{Y})}{\left\| X - \bar{X} \right\|.\left\| Y - \bar{Y} \right\|} \tag{3}$$

This correlation is used for source camera identification from an unknown image. The camera corresponding to the reference pattern giving the highest correlation is decided as the source camera. An experimental threshold can also be determined, and then camera corresponding to the reference pattern giving correlation value higher then the threshold will be decided as the source camera.

4. Experimental Results

Table 1 lists the digital still cameras used in our experiments. Each of these cameras are used to capture pictures at different resolutions and image quality settings, with all other settings left to default, such as auto focus, red eye correction and white balance. Pictures taken by using these cameras have similar as well as dissimilar contents. Figure 5 shows a sample of the images used in this study. The image dataset includes broad range of images, from natural scenes to buildings, images with different backgrounds, light intensities and so on.

	Device Brand	CCD Sensor	Sensor Resolution	Max. Picture Size	Image Format
c1	Canon PowerShot SD200-1	1/2.5 inch	3.2 MP	2048 x 1536	JPEG
c2	Canon PowerShot SD200-2	1/2.5 inch	3.2 MP	2048 x 1536	JPEG
c3	Nikon Coolpix 7600	1/1.8 inch	7.1 MP	3072 x 2304	JPEG
c4	Panasonic DMC-FZ20	1/2.5 inch	5 MP	2560 x 1920	JPEG/TIFF
c5	Nikon Coolpix 4100	1/2.5 inch	4 MP	2288 x 1712	JPEG
c6	Nokia 6630(3G smartphone)			1280 x 960	JPEG
c7	Olympus E-10	2/3 inch	4 MP	2240 x 1680	JPEG/TIFF
c8	Olympus D-360L			1280 x 960	JPEG/TIFF
c9	Panasonic Lumix DMC-FZ4-1	1/2.5 inch	4 MP	2304 x 1728	JPEG/TIFF
c10	Panasonic Lumix DMC-FZ4-2	1/2.5 inch	4 MP	2304 x 1728	JPEG/TIFF

Table 1. List of digital cameras used in experiments.

Figure 5. Sample images.

4.1 Reference Camera Pattern Generation

Reference camera patterns are obtained by averaging the noise extracted from multiple images from the same camera. It is not necessary to have the cameras in our possession as only the training images are needed and no internal design parameters need to be accessed. To determine the optimal number of training images needed to generate the camera reference pattern, 20 randomly chosen images are used as test images and the average correlations (ρ_{avg}) between the camera reference pattern generated from N_p training images and these testing images are plotted in Figure 6.

Since the correlation detector is highly sensitive to geometrical transformations such as rotation and one does not know in which way the user held the camera, we need to incorporate these causes of desynchronization when obtaining the correlation. After estimating the noise, it is rotated both +/- 90 degrees and then higher of the two correlation values is used.
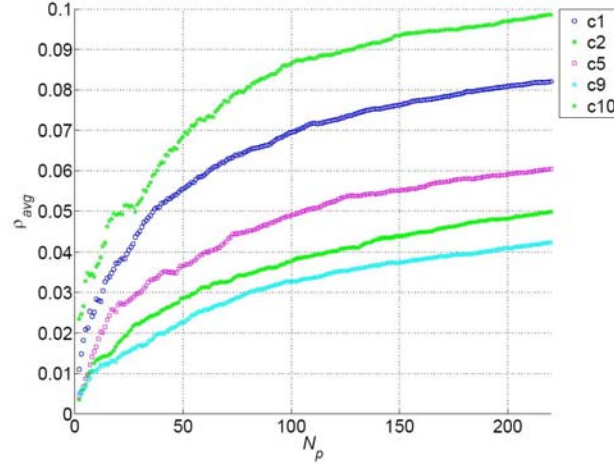
Figure 6. Average correlation ρ_{avg} as a function of the number of images N_p used for calculating the reference pattern.

4.2   Image Identification From Unprocessed Images

In these experiments on source camera identification using images of unknown origin, camera reference patterns are estimated using 200 randomly chosen training images. Figures 7, 8, 9, 10 and 11 show the correlation values for various images from a camera with the reference patterns from all other cameras. Eleven reference patterns corresponding to ten different source cameras are used. For camera c3, two reference patterns are used, one obtained from images captured at resolution 3072×2304 and second one obtained from images captured at resolution 2048×1536. This is to see the effect of sizes of the reference patterns on source camera identification. In these experiments for computing the correlation between noise patterns of different sizes, the larger of the two is always cropped from the top left corner to match the size of the smaller one. In Section 4.4, experiments are performed by resizing the images before denoising to match the size of the reference patterns. The source camera is decided based on the reference pattern giving the highest correlation value. In all cases the classification accuracy is greater than 98%. The first 200 images correspond to those used for estimation of the reference pattern and the rest are used for testing. It is to be noted that even though the correlation between noise patterns from test images and the correct reference pattern is comparatively less than correlation between noise patterns from training images and the correct reference pattern, the correlation value with the correct reference pattern is much higher than that with the incorrect reference patterns. Correlation with the correct reference pattern is much lower for images of night sky or those obtained by closing the lid of the camera lens. This observation is consistent with all the cameras.
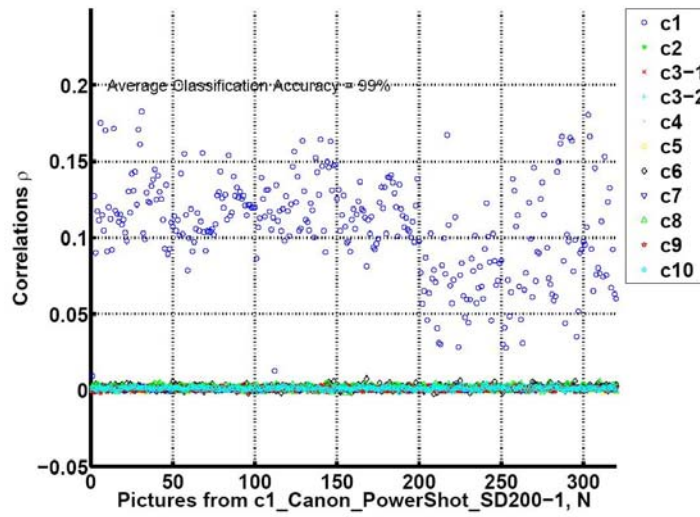
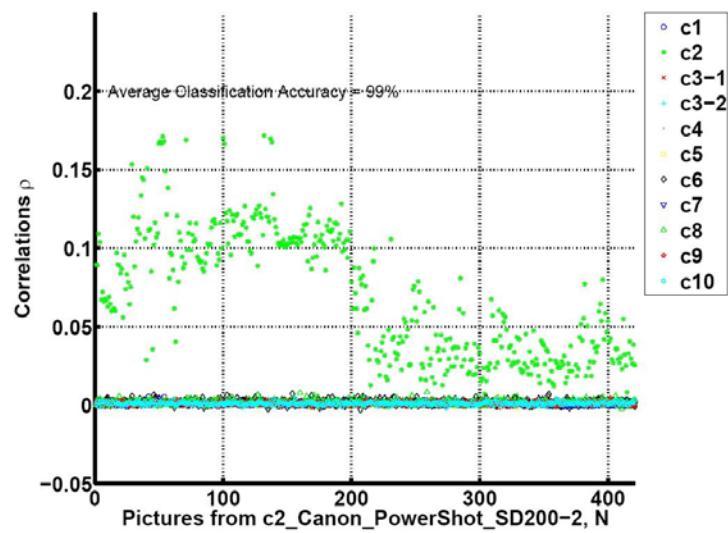Figure 7. Correlation of noise from c1 with 11 reference patterns.

Figure 8. Correlation of noise from c2 with 11 reference patterns.
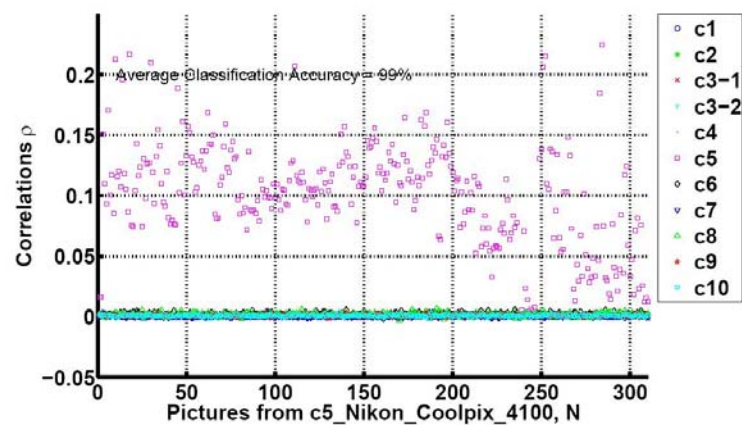
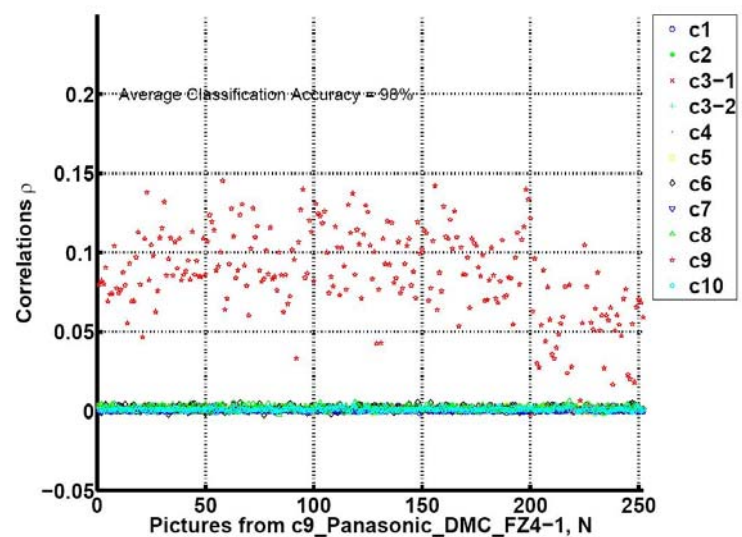Figure 9. Correlation of noise from c5 with 11 reference patterns.

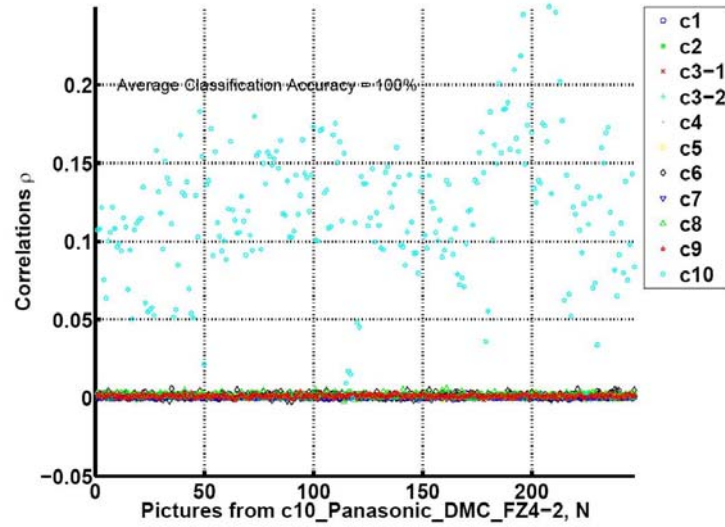Figure 10. Correlation of noise from c9 with 11 reference patterns.

Figure 11. Correlation of noise from c10 with 11 reference patterns.

4.3 Effect of JPEG Compression On Image Identification

In this set of experiments, the effect of JPEG compression on source camera identification is analyzed. Since the noise extracted using the wavelet based denoising filter corresponds to high spatial frequencies and the JPEG compression typically throws away high frequency information, the correlation between image noise and the reference patterns is expected to decrease. Experiments on different cameras show that this is indeed true. At the same time, correlation with the wrong reference patterns also decreases and accurate source camera identification is still possible.

Figures 12, 13, 14 and 15 show the variation in mean and variance of correlation between test images stored at different JPEG quality factors and the reference patterns from correct and incorrect cameras.
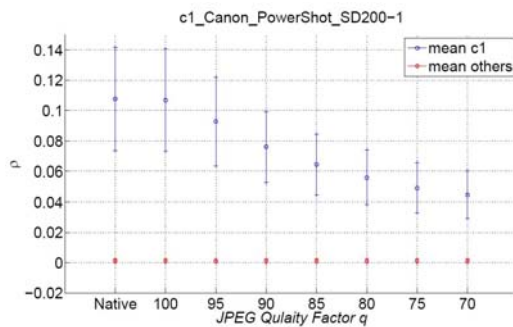

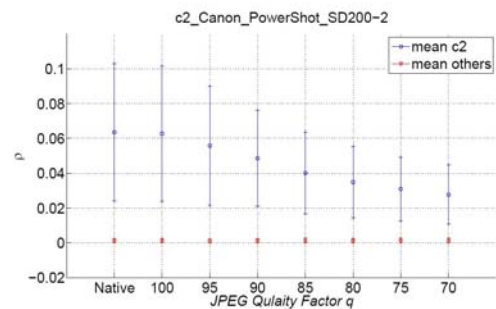Figure 12. Mean and standard deviation of ρ as a function of the JPEG quality factor.

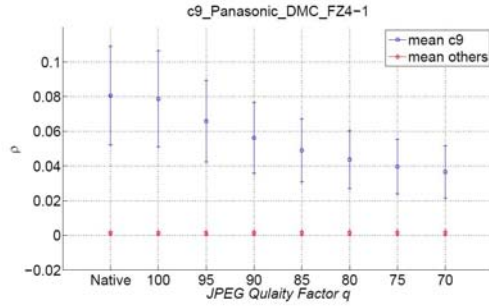Figure 13. Mean and standard deviation of ρ as a function of the JPEG quality factor.

Figure 14. Mean and standard deviation of ρ
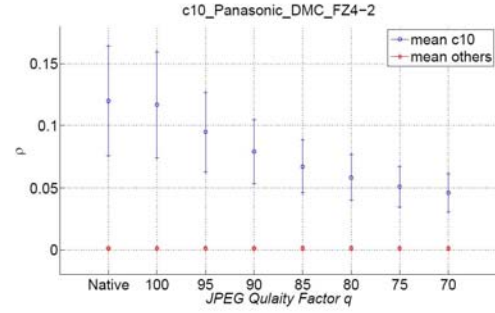as a function of the JPEG quality factor.

Figure 15. Mean and standard deviation of ρ
as a function of the JPEG quality factor.

4.4   Effect of Resampling On Image Identification

This section investigates the possibility of identifying images obtained at a resolution lower than the camera's native resolution (maximal resolution supported by the camera). Three hundred fifty images were captured using camera c1 at a resolution 1024×768. For source camera identification, we assume that these images have been captured at this lower resolution or rescaled in computer but not cropped. For source camera identification, the camera patterns estimated from images at native resolution of the camera are used. For cases when the size of the noise pattern of an image does not match with the size of a reference camera pattern, the image is resampled using "bicubic" interpolation. Noise is then extracted from this resampled image and correlated with the known camera reference patterns to determine the source camera.

As Figure 16 shows, source camera identification is possible even from images captured at non-native resolutions. In Figure 16, the reference pattern c1–1 is estimated by averaging 200 images captured at resolution 1024×768, while the reference pattern c1–2 is estimated by averaging 200 images captured at resolution 2048×1536. Since most digital cameras do not use simple resampling methods such as "bicubic" interpolation to obtain lower resolution images, the correlation of noise extracted from a 1024×768 size image is expected to be higher with the reference pattern c1−1 than with reference pattern c1−2. This is indeed true in Figure 16. Further, the correlation with the reference pattern c1−2 is consistently higher than correlation with any other reference pattern. Thus even for the cases when sizes of training and testing images are different, the classification accuracy is close to 100%, though with a smaller tolerance and thus lesser reliability.
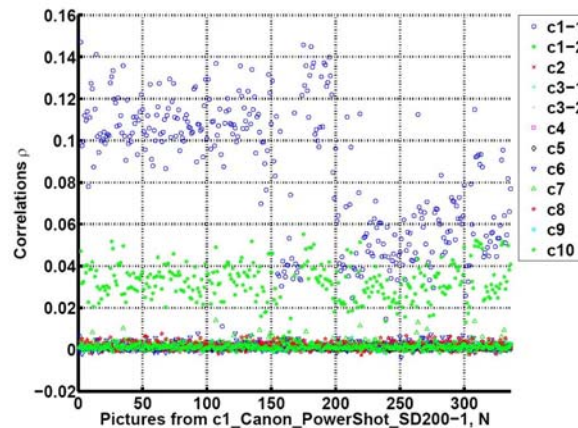

Figure 16. Identification of low resolution (1024*768) c1 Canon SD200-1 images.

Experiments to see the effect of simultaneous application of JPEG compression and resampling show similar decline in correlation values, but maintain close to 100% classification accuracy.

4.5 Effect of Malicious Processing

The issue of preventing source camera identification by removing the pattern noise from an image is addressed in this section. In the experiments performed here, noise is extracted from the denoised image and correlated with the reference patterns obtained from initial training images (as used in the earlier sections). Figures 17, 18 and 19 show the correlation values for various denoised images from a camera with the reference patterns from all other cameras. Comparing with Figures 8, 10 and 11, the correlation values for images undergone malicious processing of removing the noise is less than the correlation values with non-processed images. Even then the classification accuracy remains greater than 98%.
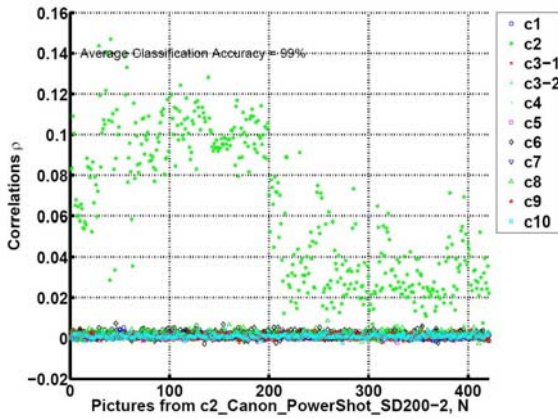

Figure 17. Correlation of denoised c2 images with reference patterns from all the cameras
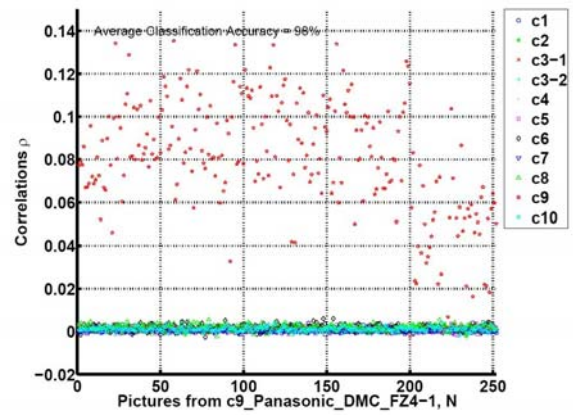

Figure 18. Correlation of denoised c9 images with reference patterns from all the cameras
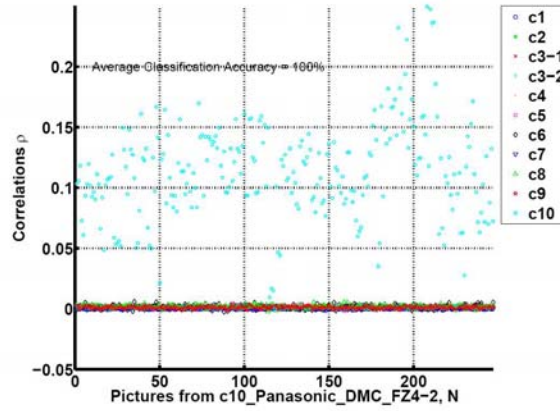

Figure 19. Correlation of denoised c10 images with reference patterns from all the cameras.

5 Conclusions

In this paper the results presented in (Lukas et al. 2005) have been verified. Figures 7-11 show that use of sensor noise and correlation detection can give close to 100% classification accuracy. Further improvements in classification with lesser number of training images can be achieved by using the improved method for reference pattern estimation presented in (Chen et al. 2007; Chen et al. 2008). In present implementation the threshold used for the correlation detector has to be experimentally determined which can be avoided by using peak to correlation energy (PCE) (Goljan and Fridrich 2008). The effect of post-processing operations such as JPEG compression, resampling and noise removal is shown in Figures 12-19. Although there is a decrease in correlation with the correct camera reference pattern, correlations with incorrect reference patterns also decrease with these operations, making successful source camera identification possible. These results show the robustness of the correlation based classification scheme presented in (Lukas et al. 2005). They also demonstrate potential problems when this scheme is used with post-processed images and the non-optimal nature of the denoising algorithm used here. Our experiments support the results presented in the original paper. We performed these experiments on our image database, using a different set of cameras and without making any contact with the previous paper's authors while developing our implementation. Since the experiments performed here were on a different set of cameras, different decision thresholds had to be experimentally determined. The camera dependent nature of these thresholds had been already indicated in (Lukas et al. 2005). The separation of correlation values for some cameras is higher than that for others (for example compare Figures 7 and 11) and it is possible to discriminate between digital cameras of the same make and model.

Acknowledgements

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Keywords
digital forensics, digital camera, sensor noise, camera forensics.

Image Captions

Figure 1. Imaging pipeline for a digital camera.

Figure 2. CFA patterns.

Figure 3. Classifier training for correlation-based approach.

Figure 4. Source scanner identification using a correlation-based detection scheme.

Table 1. List of digital cameras used in experiments

Figure 5. Sample images.

Figure 6. Average correlation ρ_{avg} as a function of the number of images N_p used for calculating the reference pattern.

Figure 7. Correlation of noise from c1 with 11 reference patterns.

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Figure 9. Correlation of noise from c5 with 11 reference patterns.

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Figure 12. Mean and standard deviation of ρ as a function of the JPEG quality factor.

Figure 13. Mean and standard deviation of ρ as a function of the JPEG quality factor.

Figure 14. Mean and standard deviation of ρ as a function of the JPEG quality factor.

Figure 15. Mean and standard deviation of ρ as a function of the JPEG quality factor.

Figure 16. Identification of low resolution (1024*768) c1 Canon SD200-1 images.

Figure 17. Correlation of denoised c2 Canon SD200-2 images with reference patterns from all the cameras.

Figure 18. Correlation of denoised c9 Panasonic DMCFZ4-1 images with reference patterns from all the cameras.

Figure 19. Correlation of denoised c10 Panasonic DMCFZ4-2 images with reference patterns from all the cameras.