OPTIMIZATION OF INPUT PATTERN FOR SEMI NON-INTRUSIVE COMPONENT FORENSICS OF DIGITAL CAMERAS

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ABSTRACT

This paper considers the problem of semi non-intrusive component forensics and proposes a methodology to identify the algorithms and parameters employed by various processing modules inside a digital camera. The proposed analysis techniques assume the availability of the camera; and introduce a forensic methodology to estimate the parameters of the color interpolation and white balancing algorithms employed in cameras. We devise testing conditions, and design good input patterns to improve the overall accuracy in parameter estimation. As demonstrated by the results in the paper, the proposed techniques provide a much lower estimation bias and variance compared to non-intrusive analysis. The features obtained from component forensic analysis provide useful evidence for such applications as analyzing technology evolution trend, detecting technology infringement/licensing, protecting intellectual property rights, and determining camera source.

Index Terms – Component forensics, semi non-intrusive forensics, visual sensors.

1. INTRODUCTION

Digital cameras have experienced a tremendous growth over the past decade. The resolution and quality of digital images have been steadily increasing, and digital cameras have become ubiquitous. Such widespread popularity has led to a growing concern about establishing the authenticity of digital photographs; and has raised a number of forensic questions related to digital camera images. For example, one can ask what kind of camera has been used to capture the image? What kinds of technology have been employed? What processing operations has the image gone through? In our recent work [1], we introduced *component forensics* as a new methodology for forensic analysis. Component forensics aims to identify the algorithms and parameters employed in various components of a digital camera. It was shown that these estimated parameters can be utilized to answer a number of questions related to the origin and authenticity of the image [2]; and to provide evidence to identify infringement/licensing and facilitate tampering detection [1].

Legal means, such as patents, for intellectual property protection has played a crucial role in fostering innovation. However, with the growing availability of sophisticated hardware and software tools, patent infringement is not uncommon. Moreover, patent infringement is typically hard to detect and there are a lack of technologies to identify substantial similarity or differences in the implementations. Often, identifying infringement becomes a laborious task, and expert witnesses may be asked to go over and compare the thousands of lines of the product's source codes. By determining the algorithms and parameters employed in different processing modules inside a digital device solely using the device's output data, component forensics provides a framework for infringement/licensing forensics and intellectual property protection. Component forensic analysis can also be extended to determine the type, brand, and model of the imaging device that was used to capture an image; and to identify potential tampering or to detect the presence of hidden data in digital photographs [1, 2].

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Component forensics can be classified into three main categories based on the amount of available evidences:
(1) *Intrusive forensics,* wherein the forensic analysts can break the device apart and analyze the intermediate signals and states for estimating the component parameters;
(2) *Completely non-intrusive forensics:* In this case, the forensic analysts do not have access to the device in hand, and only have some sample output data provided to them. The task of the forensic analysts is to then devise methods to identify the algorithms and parameters employed in the internal components of the device solely based on output data. These were studied in [1, 3];
(3) *Semi non-intrusive forensics:* This scenario is in between the completely intrusive and the completely non-intrusive cases, whereby the analysts have access to the device, and can design experiments and choose appropriate inputs to the device to increase the accuracy and overall confidence in parameter estimation without breaking the device apart.

In this work, we consider the problem of *semi non-intrusive* component forensics. Based on a detailed modeling of the imaging process and knowledge of the possible algorithms employed in such components as color interpolation and white balancing, we develop a set of desirable conditions for a good input pattern and use these guidelines to optimize the design of input pattern for semi non-intrusive forensic analysis of these components. Our simulation results show that the overall accuracy in parameter estimations can be improved significantly by this approach compared to completely non-intrusive forensics.

To our best knowledge, this is the first work to address the problem of semi non-intrusive component forensics. Related works fall into two basic categories. In the forensics literature, there have been works that aim to find the parameters of post-camera processing operations [4, 5] such as JPEG compression, resampling, and brightness change; and to non-intrusively estimate the parameters of camera components such as lens distortions, color filter array [1], and color interpolation [1, 3]. However, the accuracy of these non-intrusive techniques is limited by the nature of the available data. A second group of prior art concerns television and camera manufacturing technologies. Among these works, there have been studies that focus on designing test patterns to tune the parameter settings of television sets by analyzing its response to specific inputs [6]. However, these works are not intended for estimating the parameters of internal device components.

2. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we discuss the image capturing model for digital cameras and present our problem formulation. Fig. 1 shows an image

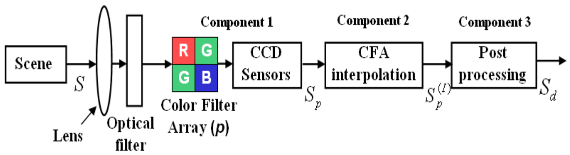

Fig. 1. Image Capturing Model in Digital Cameras showing its individual components

acquisition model of digital cameras. The light rays from a scene pass through lens and optical filters, and are finally recorded by the charge coupled device (CCD) detectors. Most digital cameras use a color filter array (CFA) to sample the real-world scene. The CFA consists of an array of color sensors, each of which captures the corresponding color of the real-world scene at sub-sampled sets of pixel locations. To facilitate discussions, let $S(.,.,.)$ be the real-world scene to be captured by the camera and let $p(.,.)$ be the CFA pattern matrix. The CFA sampling converts the scene S into S_p satisfying

$$S_p(x,y,c) = \begin{cases} S(x,y,c), & \text{if } p(x,y) = c, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

After the data obtained from the CFA is recorded, the pixel values corresponding to the points where $S_p(x,y,c) = 0$ in (1) are interpolated using its neighboring pixel values to obtain $S_p^{(I)}$. The specific color interpolation algorithm is typically kept proprietary by a camera manufacturer, and companies often employ different algorithms. In our recent work [1], we showed that parameters of color interpolation can be robustly estimated by approximating them by linear models in different regions of the image. More specifically, we divide the image regions into three classes $\Re_m, (m = 1,2,3)$, based on the gradient features in a local neighborhood, and model interpolation in each region to be linear with coefficients $\alpha_{\Re_m}$ so that

$$S_p^{(I)}(x,y,c) = \sum_{k,l} \alpha_{\Re_m}(k,l,c) S_p(x-k, y-l, c) + n_1(x,y,c), \tag{2}$$

Here, the summations over variables k and l are done in the regions where the filter $\alpha_{\Re_m}(k,l,c)$ has support, and n_1 represents the overall model-fitting error.

Such processing operations as white balancing and color correction are performed by the camera after color interpolation to ensure that a white object in the scene appears white in a photograph. White balancing operations are typically multiplicative [7, 8], and each color in the photograph is multiplied by an appropriately chosen constant in the camera color space. Using U to represent the transformation matrix that is used to convert the RGB color coefficients to camera color space, the white balancing operation can be modelled as

$$\begin{bmatrix} S_p^{(wb)}(x,y,1) \\ S_p^{(wb)}(x,y,2) \\ S^{(wb)}(x,y,3) \end{bmatrix} = U^{-1} \Lambda U \begin{bmatrix} S_p^{(I)}(x,y,1) \\ S_p^{(I)}(x,y,2) \\ S_p^{(I)}(x,y,3) \end{bmatrix}, \tag{3}$$

where $S_p^{(wb)}$ represents the white-balanced pixels, and the 3×3 diagonal matrix Λ denotes the white-balancing coefficients that are chosen based on the lighting conditions of the scene[1]. In most commercial cameras, white balancing is done in the XYZ color space [7], and U in this case would correspond to the color transformation from RGB to XYZ space. Some modern digital cameras may perform sensor sharpening, and appropriate modifications are done to the matrix U to include these effects. Note that U is tied to a camera, while the value of Λ varies for each picture taken by the device. Finally, the image may be JPEG compressed to reduce storage space.

[1]Diagonal transformation matrix is preferred for Λ as it follows the Von-Kries hypothesis[8], and has only 3 parameters to be estimated from the scene.

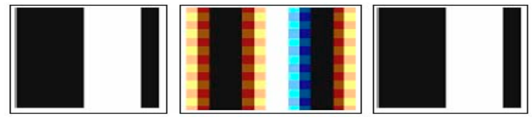

Fig. 2. Sample pattern to identify interpolation type (from left to right) (a) input image, (b) image obtained after non-adaptive interpolation; (c) image obtained after adaptive interpolation.

For the problem of semi non-intrusive component forensics, we assume that a forensic analyst has access to the camera and can perform testing in controlled conditions to determine the algorithms and parameters of the imaging components, such as color interpolation coefficients, $\{\alpha_{\Re_m}\}$, and the white balancing parameters, U and Λ. More specifically, forensic analysts can design experiments and choose the best input pattern that would enable them to estimate the component parameters. We shall show through simulations that with well-designed inputs, the overall estimation accuracy (in terms of bias and variance of the estimator) can be improved, and the amount of improvement depends on the nature of each processing component.

3. CONSTRUCTING GOOD INPUT PATTERNS

In general, choosing the best input pattern depends on the nature of the algorithms that we wish to identify. For digital cameras, there are two main classes of color interpolation algorithms depending on the handling of edge regions, namely, adaptive and non-adaptive methods [9]. Therefore, a pattern with sharp edges as shown in Fig. 2(a) would be a good input to identify the interpolation category. The corresponding images interpolated with non-adaptive and adaptive methods are shown in Fig. 2(b) and (c), respectively. The figure shows that there are significant artifacts for images interpolated using non-adaptive methods, while no such distortions are observed in the images interpolated using edge adaptive techniques. This result suggests that the input pattern in Fig. 2(a) would be a good choice to distinguish between the two categories of interpolation. However, this simple pattern may not be able to distinguish between different adaptive methods that use different filtering coefficients for interpolation.

Generalizing on this observation, we define a set of desired properties for an input pattern based on a detailed study of the imaging process and knowledge of possible algorithms employed in each processing component. We first extend the pattern in Fig. 2(a) to incorporate different types of directional edges (such as a converging edge pattern) to identify the color interpolation coefficients for these types of regions. Chirp signals are included in the input pattern to capture variations of the interpolation algorithms in frequency domain. A chirp signal $s(x,y)$ can be generated by $s(x,y) = Kcos(ax^2 + by^2)$, where K, a, and b are appropriate constants. These signals provide a systematic methodology to construct symmetric circular patterns with gradually decreasing widths, and therefore help study the nature of interpolation methods in various frequency bands.

Many cameras in the current market use the white-patch algorithm or the grey-world methods for automatic white balancing. In

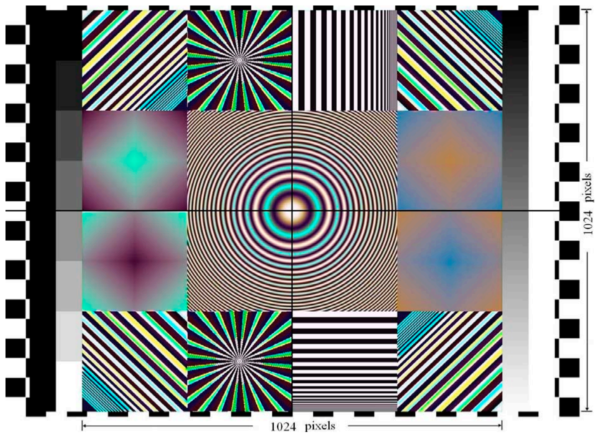

Fig. 3. Proposed Input Pattern (best viewed on a color display)

the white patch algorithm, the white balancing (WB) parameters are chosen to normalize the image pixels so that a white image appears white in a digital photograph. On the other hand, the parameters in grey-world methods are chosen to make the average pixel value close to 128 in a 8-bit image. Based on this observation, we introduce large sections of all-black and all-white regions with constant intensity, and gradually varying grey-scale regions to enable finding the parameters of WB algorithm. Finally, a gradually changing grey-scale region and long straight lines are added to facilitate estimating the parameters of gamma correction and lens distortion, respectively, and to help align the image captured by the camera with the original input pattern in the experiment.

A possible input pattern constructed based on the requirements mentioned above is shown in Fig. 3. As can be seen from the figure, it has chirp patterns at the center, and the wedge patterns have been repeated twice to help provide more information about the variability in handling gradients along different directions. Gradually changing smooth regions border the chirp patterns to help identify the interpolation methods used in smooth regions. The image has been post-processed by smoothening the hue.

4. SIMULATION RESULTS AND DISCUSSIONS

In this section, we examine the effectiveness of the proposed pattern by analyzing the parameter estimation error, and compare the results obtained with natural images under completely non-intrusive forensics scenario. For our study, we consider color interpolation and white balancing as examples for illustration.

Estimating Color Interpolation Coefficients: In the case of completely non-intrusive forensics, the analysts do not have access to the cameras, and therefore do not have control over the nature of inputs. Their forensic results are constrained by the image content provided to them. In order to simulate the non-intrusive forensic scenario for comparison studies, we select 20 representative images corresponding to different natural scenes. These images are first down-sampled to remove the effects of previously applied filtering and interpolation operations, sampled on the Bayer filter array, and then interpolated using six different interpolation algorithms to reproduce the scene capture process in cameras. The interpolation methods that we consider are: (a) Linear types of interpolation, including Bilinear and Bicubic, and (b) Non-linear interpolation methods including Smooth Hue, Median Filter based approach, Gradient based, and Adaptive Color Plane [9]. These 120 images obtained using these six different interpolation techniques form the non-intrusive forensic dataset.

For each image in the dataset, we estimate the interpolation coefficients from each type of region $\Re_m$ by solving the least squares problem [1], re-interpolate the image using the estimated coefficients, and find the estimation error. We compare the estimation results obtained semi non-intrusively using the proposed pattern with the ones got by employing natural images under non-intrusive scenarios. Fig. 4(a) and (b) compare the results in terms of the mean and variance of the estimation error, respectively, for the two linear and four non-linear interpolation algorithms. As can be seen in the figure, the proposed pattern gives an average estimation error close to 0.007 that is much lower compared to natural images for which the values are around $0.015-0.03$. This suggests the effectiveness of the proposed pattern for improving the estimation of the color interpolation coefficients and demonstrates the performance gains of semi non-intrusive forensics over the completely non-intrusive scenario.

Estimating White Balancing Parameters: It is difficult to non-intrusively estimate the white balancing parameters U and Λ accurately from the output images without the knowledge of the actual raw values captured by the sensor. However, they can be semi non-intrusively estimated. If the digital camera can produce raw images, the pixel values as captured by the CCD sensors can be read out from the captured image. These values can be used alongwith the actual white balanced output to estimate U and Λ by solving (3). For digital cameras that do not produce the raw format, the values of U can be estimated by a two-step process. The first step obtains two images with approximately the same raw data but different white balanced processed versions. This can be done by manually choosing different built-in white balancing options while taking the pictures, for example, one image with white balancing setting fixed to "tube light" and another with "tungsten light." Let the white balanced RGB pixel values in the first image be denoted as $R_{wb}^{(1)}$, $G_{wb}^{(1)}$, and $B_{wb}^{(1)}$ and let $R_{wb}^{(2)}$, $G_{wb}^{(2)}$, and $B_{wb}^{(2)}$ represent the corresponding values in the second image. Denoting the corresponding white balancing constants employed in generating the two images by $\Lambda^{(1)}$ and $\Lambda^{(2)}$, respectively, we can show that $[R_{wb}^{(2)}\ G_{wb}^{(2)}\ B_{wb}^{(2)}]^T = A_{1\to 2}[R_{wb}^{(1)}\ G_{wb}^{(1)}\ B_{wb}^{(1)}]^T$, where $A_{1\to 2} = U^{-1}(\Lambda^{(2)}/\Lambda^{(1)})U$. Here, the notation $\Lambda^{(2)}/\Lambda^{(1)}$ represents a diagonal matrix with each diagonal element obtained as an element-wise division of the corresponding terms in $\Lambda^{(2)}$ and $\Lambda^{(1)}$.

We test our proposed estimation techniques for simulated data and study its robustness to JPEG compression. To reproduce the experimental setup, we generate two images by applying two different WB parameters Λ (corresponding to the ones used for *daylight* and *tungsten light* settings) and with the same U used in the Canon EOS Digital Rebel camera. The white balanced images are then JPEG compressed with different quality factors, and the compressed images are used in estimation. The error in estimating $A_{1\to 2}$ is computed as the squared Frobenius norm between the actual and the estimated values, and is shown in Fig. 5(a) as a function of the JPEG quality factor. The figure shows the error for the synthetic pattern alongside the average error recorded from 20 natural images. The error reduces as the quality factor increases for both natural images and the designed pattern as expected. We also observe that the overall value of error for the designed pattern is an order of magnitude lower than that obtained for natural images. This result demonstrates the superiority of the proposed pattern for semi non-intrusive estimation of white balancing parameters.

Eigen value decomposition is applied to the estimated matrix $A_{1\to 2}$, and the eigenvector matrix $\hat{U}_{norm}$ is computed with each of the eigenvectors normalized to unit energy. The Frobenius norm between the actual normalized matrix U_{norm} and the estimated matrix

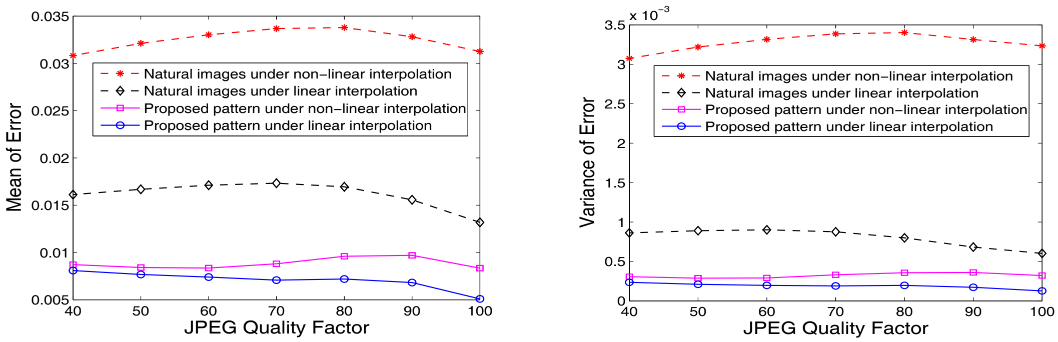

Fig. 4. Results for Color Interpolation showing (a) mean and (b) variance of estimation error.

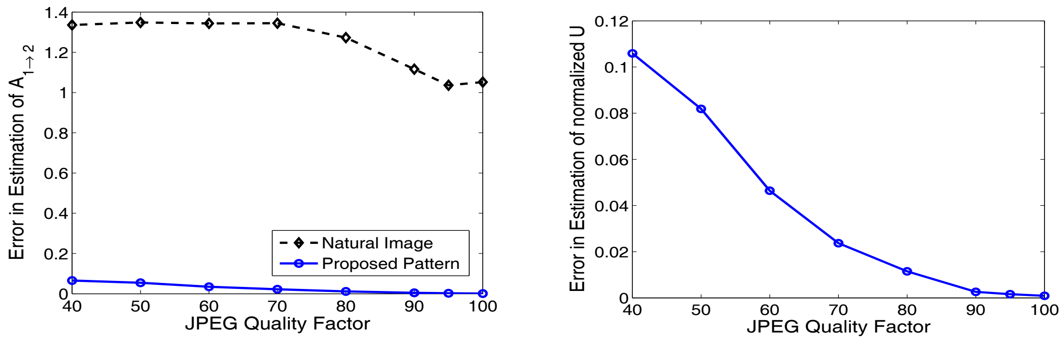

Fig. 5. Results for White balancing showing the error in estimation of (a) $A_{1\to 2}$ and (b) normalized transformation matrix U_{norm}.

is shown in Fig. 5(b) as a function of the JPEG quality factor. We notice that error values are lower than 0.1, suggesting the effectiveness of the proposed pattern for estimating the WB parameter U_{norm}. Similar results were also obtained when tested with camera data.

Comparing Fig. 4(a) and Fig. 5(a), we also find that while the estimation results obtained in the semi non-intrusive scenario with the proposed pattern are better than the ones obtained using natural images in both cases, the performance improvement is more significant in the case of white balancing than for the case of color interpolation. This result can be attributed to the multiplicative nature of the WB operation (see (3)), that requires more information to produce more accurate estimates, and such additional information may be available in controlled test conditions in a semi non-intrusive scenario. These results also suggest that the performance improvements obtained with semi non-intrusive forensics depends on the nature of processing that is to be identified.

5. CONCLUSIONS

In this paper, we consider the problem of semi non-intrusive forensic analysis of digital cameras. The proposed framework assumes the forensic analyst has access to the camera, and can therefore design controlled test conditions and better inputs to improve the overall estimation results. We identify the basic requirements of a good input pattern, and construct an input pattern satisfying these conditions. We present a systematic methodology to estimate the parameters of the cameras' color interpolation and white balancing algorithms, and show through simulations that the proposed input pattern in controlled testing conditions provides an overall higher accuracy in parameter estimation. Comparisons with natural images obtained under non-intrusive forensic conditions suggest the need for robust semi non-intrusive forensics, and the superiority of the synthesized input pattern for parameter estimation. Simulation results also demonstrate that the performance improvements obtained with semi non-intrusive forensics depends to a great extent on the nature of the algorithms to be estimated. The features obtained from such semi non-intrusive analysis provide useful evidence to analyze infringement/licensing, to construct good training sets for camera identification, and to provide ground-truth information for tampering detection.

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