Estimation of color modification in digital images by CFA pattern change

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ABSTRACT

Extensive studies have been carried out for detecting image forgery such as copy-move, re-sampling, blurring, and contrast enhancement. Although color modification is a common forgery technique, there is no reported forensic method for detecting this type of manipulation. In this paper, we propose a novel algorithm for estimating color modification in images acquired from digital cameras when the images are modified. Most commercial digital cameras are equipped with a color filter array (CFA) for acquiring the color information of each pixel. As a result, the images acquired from such digital cameras include a trace from the CFA pattern. This pattern is composed of the basic red green blue (RGB) colors, and it is changed when color modification is carried out on the image. We designed an advanced intermediate value counting method for measuring the change in the CFA pattern and estimating the extent of color modification. The proposed method is verified experimentally by using 10,366 test images. The results confirmed the ability of the proposed method to estimate color modification with high accuracy.

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1. Introduction

Recently, the performance of digital imaging devices such as digital cameras, digital camcorders, scanners and smartphones has improved drastically, while their prices have decreased. Further, continuous advances to digital image editing software such as Adobe Photoshop, Paintshop Pro, and Vegas are being made. As a result, digital images can be easily manipulated by the non-professional users. Therefore, there is a high risk of copyright violation and illegal manipulation or acquisition of images.

Digital forensics is a promising solution for these crimes. Forensics is the process of finding proof that helps in crime investigations; it also helps in analyzing and presenting proof as the legal proof in court. In forensics, examples of analog proof, whose characteristics change continuously, are dead bodies, oil paintings, bullet marks, bloodstains, etc., and those of digital proof, which can be represented as 0 or 1, are digital images stored on a hard-disk drive, scanned images, information stored on a server, etc.

Digital image forensics focuses on digital images which are comprised of image and video. Digital image forensics analysis involves two steps. First, information, such as the device type, model, and characteristics required for acquiring digital images is obtained, by considering the intrinsic signature of digital imaging devices. Second, it is determined whether the image is forged or not. In addition, the forgery method and its extent can be found. Digital image forensics is of use in detecting forgery methods on images such as copy–rotate–move, resizing, double compression, and recapturing [1]. According to our survey of literature, however, no forensics scheme can detect color modification although it is a commonly used forgery method.

There has not been accurate definition of color modification attack in digital image forensics field. In this paper, we define color modification attack as the change of the ratio between red, blue, and green channels. In other words, it is the change of the hue value. According this definition, brightness adjustment which modifies the luminance of image is not color modification attack. However, hue and white balance adjustment are to be included in this attack. These manipulations can be easily conducted with the image-adjustment menu of Photoshop.

Actually, numerous digital images have been forged for funny such as a parody, and satire [2]. For example, some people in a movie poster can be replaced by other funny people by image editing tools. In some cases, however, a forged image became big issue related with media, politics, race and gender [3]. For example, Iran copy and move one missile which is successfully launched for military purpose on 2008 [4]. For color modification attack, for instance, attacker can modify the color of human face to look like a drunken. In another example, a criminal can modify the color of his car in captured image to eliminate evidence. Especially, following event is a real example that how color modification attack is applied to distort the mass media.
Fig. 1 presents a photo of the Hatshepsut temple in Luxor, Egypt, where 58 innocent tourists were murdered in 1997. The German-language daily tabloid Blick, published in Switzerland, forged the image by modifying the color of the flooding water to red so that it can be mistaken for blood and distributed it to news channels (Fig. 1(a) and (b); before and after color modification, respectively) so that the public could understand the brutality of the attack.

In order to counter these kinds of color modification attacks, we present a novel scheme that can estimate color modification in digital images. Most commercial digital cameras are equipped with CFA for obtaining color information. Since images captured with such a camera include a trace from the CFA pattern, several researchers have carried out studies for detecting and estimating these traces [5–12]. In our study, we design an algorithm based on the fact that CFA pattern is changed if the color of digital images is changed. The digital image which is composed of RGB color is converted into a hue-saturation-intensity (HSI) image and the change in hue is measured by the newly designed intermediate value counting method. 10,366 images were used in our experiments including post-processing such as JPEG compression and image cropping to verify the performance of the proposed algorithm.

The rest of this paper is organized as follows. Section 2 explains related works on CFA patterns. Sections 3 and 4 include preliminary knowledge and the proposed method for estimating color modification, respectively. Experimental results and conclusion are presented in Sections 5 and 6, respectively.

2. Related works

To the best our knowledge, there has been no research on forgery of digital images by color modification. Since the proposed method is based on CFA patterns, prior works related to reports on CFA patterns are investigated.

Previous studies on CFA patterns can be categorized into three categories. The first category involves studies on finding the existence of interpolation trace of a test image. Popescu et al. proposed a method for detecting the interpolation trace using the expectation–maximization (EM) algorithm [5]. Gallagher et al. used the noise variance in the interpolated pixels and observed pixels [6]. They extracted the noise image using second derivatives of the image, on the basis of the supposition that the noise variance in the interpolated pixels is lower than that in the observed pixels. Takamatsu et al. improved Gallaghers method by extracting the noise image using neighboring pixels instead of the second derivative of an image [7].

The second category includes studies on the estimation of the CFA pattern of digital cameras. Swaminathan et al. proposed a method for identifying CFA patterns using the interpolation error [8]. Takamatsu et al. introduced a new criterion, the ratio of the average noise variance in all interpolated pixels to that in the observed pixels [7]. They calculated this ratio for all the candidate CFA patterns and chose the CFA pattern with the highest ratio as the true pattern. Kirchner et al. suggested an efficient forgery detection method for estimating CFA pattern based on CFA synthesis [9]. They proposed an approximate solution that requires only one linear filtering operation per image. In a recent study [10], they used the intermediate value counting algorithm to estimate the CFA patterns. This method achieved high accuracy for not only full size of digital images but also a small block of that.

The third category includes studies on the detection of the CFA interpolation algorithm. Cao and Kot proposed a new method for detecting the CFA interpolation regularity on an image by using reverse classification with the partial derivative correlation model [11]. This method can be used in forensic applications such as camera model and RAW-tool identifications. In [12], Bayram et al. combined the features of Popescu method [5] and Gallaghers method [6] for estimating the CFA interpolation coefficient.

Fig. 2. Image capture process in a digital camera.
Although CFA patterns were not considered, Stamm et al. proposed the method for detecting contrast enhancement, which can change the color of digital images slightly [13]. In pixel value mapping, a statistical trace is analyzed to detect contrast enhancement or histogram equalization of digital images. Stamm et al. applied a pinch-off function to the image histogram and calculated the normalized energy in the high-frequency components of the pixel value histogram. Then, they used this measure for detecting contrast enhancement and histogram equalization.

3. Preliminary

We present some preliminary knowledge that would help in gaining a deeper understanding of our method. Since the scope of the proposed method is limited to images captured by a digital camera equipped with a CFA, we explain about the image capture process in brief [14].

3.1. Image capture process in a digital camera

Fig. 2 shows the process of capturing images using a digital camera. Light from the scene passes through the lens which transmits the light by converging it. At this time, light cannot be perfectly converged at the single point because there is a not completely accurate model [15]. This error is known as aberration. There are two types of aberration: monochromatic aberration and chromatic aberration.

Geometry of the lens is main reason of monochromatic aberration. Therefore, color is not related with this aberration. It includes spherical aberration, coma, astigmatism, Petzval field curvature, and distortion. Among the distortion, radial distortion of different camera models are different each other. Based on this fact, Choi et al. proposed the method to identify the source camera model using radial distortion as footprints [16].

Chromatic aberration is caused by different reflective index of the lens for each wavelengths of light. The degree of chromatic aberration is also different for camera models and some digital image forensic methods use this flaw as footprints [17–19].

After pass the lens, light passes various filters such as anti-aliasing filter, and infrared cut-off filter. Anti-aliasing filter blurs the incoming image and this filter is also known as low-pass filter or blur filter. Actually, the size of image sensor cell is too big to be capable of detail natural scene, and acceptable resolution is limited. For example, Moire pattern will be appeared in a digital image including a striped pattern shirt which has very small interval. To solve this problem, an anti-aliasing filter blurs detail natural scene until an image sensor does not has aliasing. Infrared cut-off filter block out the infrared light as the name suggests. Image sensor responds to visible and infrared light simultaneously. Since human visual system only accept visible light and most people wants the digital image that they actually see as much as possible, most commercial digital camera equipped an infrared cut-off filter.

Most image sensors measure light intensity but cannot identify the color information. Hence, the CFA is located in front of the image sensor for separating color information. The CFA looks like cellophane, which allows light of the desired color to pass through. For example, light passing through a red filter includes only the red component, and hence, the image sensor can recognize the light color as red. Among various CFA patterns, the Bayer pattern [20] is widely used in commercial digital cameras as shown in Fig. 3. The Bayer pattern has two green channels and one channel each of red and blue, as the human eye is more sensitive to green light than to red and blue light. There are unusual CFA patterns such as RGBE, CYYM, CTGM, and RGBW which are equipped in only few camera models of Kodak and Sony. Distinctively, Foveon X3 direct image sensors can directly capture red, green, and blue light without CFA [21]. In this paper, we consider only Bayer patterns as they are widely used in commercial digital cameras.

Finally, light passed through CFA arrives an image sensor. There are two types of an image sensor: charge-coupled device (CCD), and complementary metal-oxide-semiconductor (CMOS) [22]. Both of them have many types of noise while sense the light. Fig. 4 outlines the sensing process with the noise introduced at each step.

Random noise refers to random pattern changed from image to image. Photon noise and reset noise belong to this type of noise. Pattern noise refers to any pattern that does not vary from frame to frame. They vary from pixel to pixel. It is called fixed pattern noise (FPN). Differences in detector size, doping density, and foreign matter can cause this noise. Because noise is unnecessary to digital camera manufacturers, they make an effort to suppress noise by a calibration and many post processing. However, in spite of their struggle, there still remains some noise in photographed images.
Among these noise, photo response non-uniformity is temporally constant fixed pattern, and it depends on each image sensor. Since PRNU is clearer than other types of noise, it is often used as footprint in digital image forensic field [23,24].

The raw image can be obtained once, the light intensity is measured. Since light has a color temperature, light affects the raw image. Raw images become red tinted at low color temperatures and blue tinted at high color temperatures. To display the white object as real white color, the white balance process is performed. Since raw images have many empty pixels, CFA interpolation is performed to fill them. Many CFA interpolation methods [25–27] have tried to make digital images more natural scene. In most of CFA interpolation algorithms, interpolated pixels are affected by neighboring pixels. Fig. 5(a) shows the most heavily affected neighbor pattern of the green channel, which has two positions in CFA pattern. This pattern is named Cross in this paper. In case of the red and blue channels, three patterns, Vertical, Horizontal, and Quincunx, greatly affect an interpolated pixel as depicted in Fig. 5(b). Some previous studies used this fact to present a new method for estimating the CFA pattern of a digital image [7,10].

3.2. Hue

Hue is an attribute of colors that permits them to be classified as red, yellow, green, blue, or an intermediate between any contiguous pair of these colors [28]. The related properties of hue are chroma, saturation, lightness, and brightness. There are many hue-based color models such as the HSI, HSV, and HSB (H: hue, S: saturation, I: intensity, V: value, and B: brightness). Fig. 6 shows a sample image with the hue cyclically shifted in the HSI color space.

A digital image is usually stored in RGB channels. Preucil describes a color hexagon [29] that can be used for computing the hue of images in the RGB channel, as shown in Eq. (1). In the hexagon, red is placed at 0°, green at 120°, and blue at 240°.

\[ \tan(h_{\text{rgb}}) = \frac{\sqrt{3}}{2} \cdot \frac{(G - B)}{R - G - B} \]  

Preucil also described a color circle, which is similar to the color hexagon and can be used to compute the hue of images in the RGB channel, as shown in Eq. (2).

\[ h_{\text{rgb}} = \begin{cases} 60 \cdot \frac{R - G}{B - R} & R \geq G \geq B \\ 60 \cdot \frac{G - B}{R - B} & G \geq R \geq B \\ 60 \cdot \frac{B - R}{G - B} & B \geq G \geq R \\ 60 \cdot \frac{G - R}{B - G} & B \geq R \geq G \\ 60 \cdot \frac{B - G}{R - B} & R \geq B \geq G \end{cases} \]
If the RGB channel values are equal, a denominator such as \((R - B), (G - B),\) and \((B - G)\), becomes 0 and it is not defined. In this case, the light is achromatic, i.e., the values of RGB channel are same and the hue value is meaningless. In this study, Eq. (2) is used for hue transformation and achromatic colors are not considered.

3.3. JPEG compression

JPEG compression is commonly used to compress images in most digital cameras [30]. In JPEG compression encoding process, an RGB digital image is converted into a \(YCbCr\) color space image. \(Y\) represents the brightness of the pixel, and \(C_y\) and \(C_b\) represent blue-difference and red-difference of the chroma components, respectively. Since the human eye is sensitive to changes in brightness, it is necessary to make a difference in compression strength between brightness and chroma components; therefore the aforementioned image conversion is effective for image compression. After the conversion, the \(C_y\) and \(C_b\) channels are down-sampled, where the \(Y\) channel, which the human eye is sensitive to, is usually maintained.

After chroma down-sampling, each channel is split into minimum coded unit (MCU) blocks. Discrete cosine transform (DCT) is applied to each block, and the DCT coefficients are quantized. Through this process, high-frequency information, to which the human eye is insensitive, is eliminated. This quantization process can affect the tracing of the CFA pattern that is based on adjacent pixel information.

4. Proposed method

The overall procedure followed in the proposed method is depicted in Fig. 7. First, the hue value of the suspicious image is changed from 0° to 359° by step of interval factor \(\Delta\). For RGB channels, the advanced intermediate value counting (AVC) table is calculated by applying the AVC algorithm. The new measure \(R', G', B'\) which is representing the counting ratio between an interpolated pixel and an observed pixel are calculated from the AVC table, where \(r\) is the change in the hue angle. By calculating \(R', G', B'\) for all changes in the hue angles, a hue shift graph can be generated as shown in Fig. 7. Finally, the graph is analyzed and the hue shift is estimated. In the following section, the basic concept and the sub-processes are explained in detail.

4.1. Basic idea

As mentioned in the previous sections, most commercial digital cameras include a CFA for generating color image. Light passing through the CFA pattern is mapped to the image sensor, and the strength at each image sensor cell represents the RGB value, depending on the CFA pattern. As a result, the empty pixels in each RGB channel model, i.e., pixels that are not mapped to the CFA pattern, should be interpolated. From this process, it can be concluded that there exists a trace of CFA patterns in digital images. Several researchers have attempted to estimate the shape of the CFA pattern from one digital image on the basis of the aforementioned trace [7–10]. It is noteworthy that the trace of the CFA pattern, which is closely related to the color information, is changed when the color of the image is modified. Fig. 8(a) shows the original CFA pattern. When the color is changed by modifying the hue by about 120°, the trace is also changed by about 120°. As a result, red, green, and blue are changed to green, blue, and red, respectively, as shown in Fig. 8(b). On the basis of this observation, we developed a novel algorithm for estimating color modification in digital images acquired from most commercial digital cameras.

4.2. Hue shift in a suspicious image

Assume that the color of a suspicious image is modified. Then, the green color in the trace of the CFA pattern will be changed to a different color. For example, when the hue of the original image is changed by about 120°, green color in the CFA pattern will be changed to blue color. Hence, we can find the green color pattern of the original CFA pattern in the blue channel of the color-modified image. When the hue of the original image is changed by about 240°, green color in the CFA pattern will change to red. When the hue of the original image is changed by about 60°, the green color pattern of the CFA pattern can be found partly in the blue channel and partly in the red channel. Since the hue value changes from 0° to 359°, the difference

![Fig. 7. Overall process of the proposed method.](image)

![Fig. 8. Original CFA pattern and shifted CFA pattern with 120°. Note that there are two blue channel instead of green channels in (b).](image)

![Fig. 9. Relationship between hue with maximal saturation in HSI and corresponding RGB intensity. 0° means red, 120° means green, and 240° means blue. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)](image)
between the changed color and the original color is the most prominent at $180^\circ$. If the hue is changed again by about $180^\circ$, the original color is observed. Fig. 9 shows the plot of RGB intensity versus hue value.

To estimate the amount of hue shift, the hue value of the suspicious image is changed from $0^\circ$ to $359^\circ$ at intervals of $\Delta \theta$. For each hue-shifted color image, we conduct the AIVC algorithm to find out the green channel of CFA pattern. If the hue shift in the modified image can be reversed by the same amount, the green color pattern of the CFA pattern can be found at the location of the green channel. If interval factor $\Delta \theta$ is small, the accuracy of the hue-shifting estimation increases but the computational cost also increases. If interval factor $\Delta \theta$ is large, the computational cost decreases but the accuracy of the hue-shift estimation decreases.

4.3. AIVC algorithm

In [10], they have developed an algorithm for estimating the CFA pattern of digital images. In this paper, this algorithm is modified for effective estimation of the extent of color modification.

Before describing algorithm theoretically, we explain it intuitively with examples. Fig. 10 shows the example of CFA pattern and corresponding pixels. In case of green channel, the value of $G(2, 2)$ is empty. By intuition, it looks natural that the value of $G(2, 2)$ is the average of neighbor pixels: $G(1, 2), G(2, 1), G(3, 2), G(2, 3)$. Bilinear interpolation algorithm, the widely used and simple interpolation algorithm, is based on this intuition. The two-dimensional mask for green channel of the bilinear interpolation algorithm is as following Eq. (3).

$$h_i h_j = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Since $G(2, 2)$ is an averaged value of neighbor pixels, it is smaller than the maximum value of neighbor pixels and bigger than the minimum values of them. In other words, it is the intermediate value of them. In this example case, the value of $G(2, 2)$ is 138.75 and it is larger than maximum value of $G(1, 2), G(2, 1), G(3, 2), G(2, 3), 140$, and smaller than minimum value of them, 135. In case of bilinear interpolation algorithm, this condition is satisfied on all occasions [10].

Bicubic algorithm, also widely used interpolation algorithm, uses farther additional pixels rather than bilinear interpolation algorithm as shown in

(a) A sample image from Nikon D90(GBRG) without hue shift

(c) A sample image from Canon 500D(RGGB) without hue shift

(b) $R'$, $G'$, $B'$ of (a)

(d) $R'$, $G'$, $B'$ of (c)
In this algorithm, interpolated values are not perfectly intermediate value because of minus values in the mask. However, approximately 98% of the interpolated values are satisfied [10] and it is enough to develop the proposed method. In case of other interpolation algorithms, they also mostly used neighbor pixels, and they are also capable of providing enough information to develop the proposed method.

On the contrary to this, it is not clear that an observed pixel is intermediate value if we assume that distribution of natural image is unknown. However, if a pixel is not an intermediate value, this pixel should be observed. In [10], they count the number of the intermediate values and this algorithm includes the parts of observed pixels. In this paper, we only count the case that a pixel is not an intermediate value, and it makes the count information more reliable.

Assume that $I_{ij}$ is the pixel value at an image coordinate $(i, j)$. We define the maximum and minimum value of each channel for neighbor pixels as follow Eq. (5).

$$\begin{align*}
\text{MIN}_{ij} &= \min(h_{ij-1}, h_{ij}, h_{ij+1}, h_{ij+2}) \\
\text{MAX}_{ij} &= \max(h_{ij-1}, h_{ij}, h_{ij+1}, h_{ij+2})
\end{align*}$$

In addition, we define an intermediate value condition for each channel, as given in Eq. (6).

$$\begin{align*}
\text{MIN}_{tj} \leq I_{ij} \leq \text{MAX}_{tj}
\end{align*}$$

We define simple propositions $p$ and $q$ as below.

- Proposition $p$: a pixel is CFA interpolated.
- Proposition $q$: the intermediate value condition is satisfied.

As explained in [10], the implication $p \rightarrow q$ is true for the nearest-neighbor and bilinear interpolation methods. The contrapositive of this implication --$q \rightarrow \neg p$ is also true under the same condition. $\neg p$ implies that a pixel is observed by an image sensor. $\neg q$ implies that the intermediate value condition is not satisfied. On the basis of this implication, we improve the intermediate value counting algorithm for the green pattern, as shown in Algorithm 1.

Since the green pattern which has two positions and the trace of the pattern is stronger than that of other color pattern, and only the positions of the green pattern in the CFA pattern trace are considered in this study. Some researchers also considered the green pattern first for the same reason [9,10]. We conduct Algorithm 1 for each channel. As a result, $2 \times 2$ AVIC tables for each channel can be obtained: $CFA_{0,0}$, $CFA_{0,1}$, and $CFA_{0,2}$.

**Algorithm 1 (AVIC algorithm for the green pattern of green channel).**

```plaintext
CFA_{a,b} \leftarrow 0 \text{ for all } a, b \text{ where } a \in \{1, 2\}, b \in \{1, 2\} 
for all pixel in $G_{ij}$ do
    if $\text{MAX}_{ij} < G_{ij}$ or $G_{ij} < \text{MIN}_{ij}$ then
        if $(i+j) \mod 2 = 0$ then
            $CFA_{1,1} \leftarrow CFA_{1,1} + 1$
            $CFA_{2,2} \leftarrow CFA_{2,2} + 1$
        else
            $CFA_{1,1} \leftarrow CFA_{1,1} + 1$
            $CFA_{2,2} \leftarrow CFA_{2,2} + 1$
    end if
end for
```

4.4. Ratio between counting values

For each channel, the total counting numbers of the AVIC tables are different. To normalize the total counting value, we define a simple criterion $K'$, $G'$, $B'$, as shown in Eq. (7).

$$K' = \frac{CFA_{1,1}}{CFA_{2,2}}$$
$$G' = \frac{CFA_{1,1}}{CFA_{2,2}}$$
$$B' = \frac{CFA_{1,1}}{CFA_{2,2}}$$

As described in Section 4.2, the hue shift with an interval of $\Delta S$ is carried out on the target image. We compute $K'$, $G'$, $B'$ for all hue-shifted images. There are two types of CFA patterns: GXXX and GXXG (X: unknown color channel). In the case of GXXX, $G'$ is the highest when the hue shift is close to 0. Fig. 11(b) shows the ratios in a sample image acquired from Nikon D90 equipped with a CBGR CFA pattern (see Fig. 3(c)) with $\Delta S = 1$. Since $CFA_{1,1}$ is an observed pixel of the CFA channel, its value is large and that of $CFA_{2,2}$ is small with no hue shift. As a result, $G'$ is the maximum at 0°, $K'$ is the maximum at 240° hue shift because the CFA pattern trace for the green channel is transformed into that for the red channel. Similarly, $B'$ is the maximum at 120° hue shift.

In case of GXXG, $G'$ is the minimum at around 0°. Fig. 11(d) depicts a graph of the ratio $G'$ with $\Delta S = 1$ and the sample image acquired from Canon 500D equipped with a RGCB CFA pattern (see Fig. 3(a)).

If there is a raw format of an image, CFA pattern can be easily extracted from the meta-data of a raw file. In practical situation, however, most of digital images are distributed as JPEG format. Since exchangeable image file format (Exif) data of JPEG format does not contain CFA pattern information, we cannot know the position of G channel of CFA pattern. In this case, camera model information can be extracted from Exif of JPEG format, and corresponding CFA pattern can be investigated. TIFF format, used in Section 5.3 also has Exif. If the meta-data is not reliable, we should find out the location of G channel based on only image data. In future, we plan to improve this point.

4.5. Estimating the shifted hue

Using the value calculated above, the amount of the hue shift can be manually estimated from the graph. When the CFA pattern is obtained from undamaged metadata, the amount of hue shift can be automatically estimated. For this automatic estimation, the maximum $G'$ is searched from among the $G'$ values in the graph when the CFA pattern is GXXG.

Let the searched hue degree with the maximum $G'$ is $H_m$, the estimated hue $H_e$ from the suspicious image can be calculated as follow Eq. (8)

$$H_e = \text{MOD}(360 - H_m, 360)$$

Similarly, when the CFA pattern is GXXG, $H_e$ of the suspicious image can be calculated by searching for the minimum $G'$ in the graph.

5. Experimental results

In our experiment, 2872 raw images were interpolated by four interpolation algorithms and a total of 10,366 test images were used excepting achromatic color images. The change in the hue of a digital image from 0° to 359° at 45° intervals can be effectively estimated by the proposed method. When the image is cropped from 512 × 512 to 16 × 16, the proposed method performs well except in the case of images cropped to 16 × 16 pixels. Practically, in many digital image forgery methods, a specific object is selected and its color is changed. In our experiment for practical, an entire image was sliced into small 32 × 32 blocks and the forgery in each block was estimated. The estimated hue shift was mapped by using pseudo color of hue. The proposed method does not estimate the change in hue.
Table 1
Digital camera models in our experiments.

<table>
<thead>
<tr>
<th>Model</th>
<th># images</th>
<th>Resolution</th>
<th>CFA pattern</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nikon D200</td>
<td>750</td>
<td>3904 × 2616</td>
<td>RGGB</td>
<td>N1</td>
</tr>
<tr>
<td>Nikon D70</td>
<td>369</td>
<td>3040 × 2014</td>
<td>BGGR</td>
<td>N2</td>
</tr>
<tr>
<td>Nikon D70s</td>
<td>367</td>
<td>3040 × 2014</td>
<td>BGGR</td>
<td>N3</td>
</tr>
<tr>
<td>Nikon D90</td>
<td>343</td>
<td>4352 × 2888</td>
<td>GBRG</td>
<td>N4</td>
</tr>
<tr>
<td>Canon 500D</td>
<td>379</td>
<td>4752 × 3168</td>
<td>RGGB</td>
<td>C1</td>
</tr>
<tr>
<td>Sony a380</td>
<td>382</td>
<td>4600 × 3064</td>
<td>RGGB</td>
<td>S1</td>
</tr>
<tr>
<td>Olympus E420</td>
<td>282</td>
<td>3720 × 2800</td>
<td>RGGB</td>
<td>O1</td>
</tr>
</tbody>
</table>

accurately at a JPEG quality factor under 97 but reasonably good results at high-quality JPEG compression.

5.1. Experimental setup

Raw images were captured by seven commercial digital cameras. CFA interpolation was carried out using dcrw, which is a raw image decoder. Four CFA interpolation algorithms supported by dcrw were used: bilinear interpolation, variable number of gradients (VNG) interpolation, patterned pixel grouping (PPG) interpolation [31] and adaptive homogeneity-directed (AHD) interpolation [32]. The hue of the sample images was shifted from 0° to 359° in steps of 45° to generate a test image set by colorspace in MATLAB [33]. Δs was set as 5.

Since some images have achromatic color, color modification attacks are meaningless. To detect the achromatic images, the standard deviation between the RGB channels was calculated, and images which have this value below 5 were discarded.

Seven digital cameras were used in our experiments, as shown in Table 1. Sample images acquired from Nikon D200, Nikon D70, and Nikon D70s were collected in the Dresden Image Database [34] for digital image forensics. The other sample images acquired from Nikon D90, Canon 500D, Sony a380, and Olympus E420 were captured in our laboratory. Totally 11,488 test images (2872 × 4) were used in this experiment, and 1122 images were discarded as they were achromatic color. Fig. 12 shows the sample images used in our experiments. All license plates in this paper were blotted out by Mosaic filter for privacy.

5.2. Interval factor Δs

Sample images were cropped by 512 × 512 size in this section. We set interval factor Δs as 1–20 by step of 1. The hue of test images was shifted by prime numbers, 127° and 251° so that the multiples of interval factors are not match with them. The root mean square error (RMSE) was calculated for each interval. The RMSE can be calculated as follow Eq. (9).

\[
RMSE = \sqrt{E((H_f - H_a)^2)}
\]

where \(H_f\) is the hue degree for color modification of forged images and \(H_a\) is the hue degree estimated by the proposed algorithm. The performance of the proposed algorithm was good when the value of RMSE is small.

Fig. 13 shows the average RMSE of 127° and 251°. As interval factor Δs is increasing, RMSE is also increasing. For small interval factors Δs < 8, the values of RMSE are similar as approximately 6. It means that the limit of precision of the proposed method is approximately below 8. In other words, even though interval factor Δs is set under 8, it is hard to achieve more fine results. However, 8° is 2.2% error of 360° and it is enough to detect forged digital image by color modifications. Especially, if the multiple of interval factor is close to shifted value, the value of RMSE can be noticeably decreased.
Table 2
The estimated mean, standard deviation, RMSE for each interval.

<table>
<thead>
<tr>
<th></th>
<th>0°</th>
<th>45°</th>
<th>90°</th>
<th>135°</th>
<th>180°</th>
<th>225°</th>
<th>270°</th>
<th>315°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.3154</td>
<td>49.2871</td>
<td>94.1226</td>
<td>139.4130</td>
<td>184.1622</td>
<td>229.3778</td>
<td>274.0806</td>
<td>319.3455</td>
</tr>
<tr>
<td>RMSE</td>
<td>3.9198</td>
<td>5.8380</td>
<td>5.7294</td>
<td>5.8970</td>
<td>5.7496</td>
<td>5.8866</td>
<td>5.7090</td>
<td>5.8749</td>
</tr>
</tbody>
</table>

![Estimated mean and standard deviation graph](image)

Fig. 14. Error bar graph with the estimated mean and standard deviation.

5.3. Color modification without combined attacks

Sample images of 1024 × 1024 size were used in this section. From Table 2, it can be seen that the mean of the estimated attack strength is almost similar to the strength of the actual attack. Estimated mean and standard deviation are also graphically described in Fig. 14.

To investigate the influence of the camera models and CFA interpolation algorithms, the values of RMSE for each hue degree are averaged, as shown in Table 3. The results of the VNG interpolation algorithm in the study [10] are more disappointing than those of other interpolation algorithms, and the results have a strong influence on the proposed method, as shown in Table 3.

5.4. Block size

The center regions of the sample images were cropped by 512 × 512, 256 × 256, 128 × 128, 64 × 64, 32 × 32, and 16 × 16. Since the CFA pattern is a 2 × 2 block, sample images were cropped by considering the even locations. The RMSE was calculated for each hue degree. Fig. 15 shows the RMSE of each block size. Since the small block included a smaller amount of counting information than did the big block, it was more disappointing. On the contrary, forged regions can be detected in smaller blocks more precisely. It is trade-off issue between the block size and the precision for detecting forged region. In our experiment in Section 5.6, we chose 32 × 32 blocks because the performance of 16 × 16 is dramatically decreased in comparison with 32 × 32.

5.5. JPEG compression

Usually, downsampling reduces the image resolution by a factor of 2 in the horizontal and vertical directions. The

![RMSE for JPEG compression mode](image)

Fig. 16. RMSE for JPEG compression mode (*uncompressed, 2L:2C: no downsampling, 2L:1C: chroma downsampling, 1L:2C: brightness downsampling).

Table 3
RMSE for each camera models and CFA interpolation algorithms.

<table>
<thead>
<tr>
<th></th>
<th>N1</th>
<th>N2</th>
<th>N3</th>
<th>N4</th>
<th>C1</th>
<th>S1</th>
<th>O1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>3.8513</td>
<td>4.1621</td>
<td>3.8192</td>
<td>3.8768</td>
<td>1.8858</td>
<td>2.9469</td>
<td>1.6066</td>
</tr>
</tbody>
</table>
The proposed algorithm estimates the trace of the CFA pattern on the basis of the relationship between adjacent pixels. Since downsampling can damage the trace of the CFA pattern, the performance of the proposed algorithm against JPEG compression was needed to be measured. JPEG compression for downsampling was performed using Advanced JPEG Compressor 2012 with compression level 1 (lowest compression ratio), downsampling options were controlled, and other options were set to default values with cropped image by size of 512 × 512.

As shown in Fig. 16, only little performance degradation is observed when downsampling was not performed. However, with chroma downsampling, the RMSE increases by around 20 and the performance of the proposed algorithm is degraded. When the brightness is downscaled, the RMSE increases considerably, although such an option is uncommon.

In order to investigate the effect of the quantization process on the proposed method, we cropped the test images by 512 × 512 pixels, compressed them by varying the JPEG quality factor from 60 to 100 using libjpeg [35], and tested the proposed method for detecting color modification. Fig. 17 depicts the plot of the RMSE values versus different JPEG compression qualities. The performance in the case of JPEG quality factors 100, 99, and 98 were acceptable. However, the RMSE at other factors increased largely. Therefore, it was understood that the performance of the proposed algorithm is satisfactory at high-quality JPEG compression but unsatisfactory at low-quality compression. In the future, we plan to carry out studies on enhancing the performance of the algorithm against this kind of low-quality compression.

5.6. Forged region detection

We forged the color of some sample images with Adobe Photoshop CS5 (64 bit). The suspicious image was sliced into a small 32 × 32 blocks.

![Fig. 17. RMSE for each JPEG compression quality: 100–60 (*uncompressed).](image)

![Fig. 18. The color of red car is transformed into cyan color by hue/saturation command in Photoshop CS5.](image)
Fig. 19. To investigate performance against multiple color modification. 4 different colors are transformed into red color. In forgery, above 2 tags include white middle band, below 2 tags not include them.

Fig. 20. Color of banana stalk is transformed into green color by alpha channel function and gradient tool of Photoshop to look unripe banana.
After the color of the sample image is modified in parts using Photoshop CS5 with the hue/saturation command, the proposed algorithm is applied; the result for the detected forgery is depicted in Fig. 18(d). To show the detected angle, the angle is mapped to the pseudo color with hue. Further, for investigating the false-positive response, the proposed algorithm was applied to the original image (without color modification), as shown in Fig. 18(b). Although some false-positive regions exist, the detected regions are not continuous, and their size is small enough for them to be filtered. As shown in Fig. 18(d), the proposed algorithm can accurately detect the color-modified region.

To measure the performance of the proposed algorithm against hue shifting at multiple angles in a single image, we acquired an image using Olympus E420, as shown in Fig. 19(a), where four colors in the Post-it tag, except the color in the middle, are modified. Two tags below include the white field for modification. Two tags below exclude the white field for modification. As shown in Fig. 19(d), the proposed method can detect multiple angles and performs well when applied to white field images because they are actually colored and not pure white.

As shown in Fig. 20, for measuring the performance against color modification using a gradient, an image of a banana was acquired with a SONY α380 camera. The stalk of the banana is changed to green using the alpha channel and the gradient tool of Photoshop CS5. As shown in Fig. 20(d), the proposed method can successfully detect the color modification on the basis of the gradient at the stalk of the banana.

From these experimental results, it can be concluded that the proposed method can successfully detect color modification attacks occurred in conjunction with other attacks.

6. Conclusion

Digital forensic researches have been pursued for detecting image forgery such as copy-move, resampling, blurring, and contrast enhancement. However, there is no reported forensic method for detecting color modification, although it is a common manipulation. In this paper, we propose a method for estimating the color modification of a digital image acquired from a digital camera. Most commercial digital cameras have a CFA that leaves a pattern trace on digital images. When the color of a digital image is modified, the CFA pattern trace consisting of RGB channels is also modified. This change in the CFA pattern trace is estimated using the AIVC method. From this information, the change in hue is estimated using the ratio between the counting values.

Experimental results show that the proposed method achieves high performance to estimate color modification. Also the results prove that the proposed method can be used to find doctored region with color in digital images.

This study is the first attempt at quantitatively estimating the color modification of images acquired from digital cameras. In the future, we plan to improve the proposed method against JPEG compression, resizing, and rotation. We also make the proposed method more reliable when the meta-data of image format is broken or doctored.

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References