IDENTIFYING SOURCE CELL PHONE USING CHROMATIC ABERRATION

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ABSTRACT

Chromatic aberration is the phenomenon where lights of different wavelengths fail to converge at the same position on the focal plane. There are two kinds of chromatic aberration: longitudinal aberration causes different wavelengths to focus at different distances from the lens while lateral aberration is attributed to different wavelengths focusing at different positions on the sensor. In this paper, we estimate the parameters of lateral chromatic aberration by maximizing the mutual information between the corrected R and B channels with the G channel. The extracted parameters are then used as input features to SVM classifier for identifying source cell phone of images. By considering only a certain part of the image when estimating the parameters, we reduce the runtime complexity of the algorithm dramatically while preserving the accuracy at high level.

1. INTRODUCTION

With the increasing popularity of cell phones equipped with camera in recent years, so does the need to accurately identify the source cell phone of a given digital image. Multimedia forensics uses multimedia objects to trace back to the original digital device which created the objects. This kind of identification would be useful in legal disputes such as claiming of multimedia assets ownership (copyright), and more importantly, being used as digital evidence in the court.

There are currently a limited number of source camera identification methods. These methods explore different parts or processing stages of the digital camera to find the clues that can help identifying correctly the source camera. They can be roughly classified into four approaches based on the camera parts that they examine.

The first approach takes advantages of camera lens distortions. Choi et al [1] measure the lens radial distortion and use it as a fingerprint to identify source camera. Radial distortion parameters are estimated using the straight line method which extracts the distorted line segments and measures the distortion error between the distorted line segments and the corresponding straight lines.

The second approach distinguishes the cameras through the imperfections of image sensors. Lukas et al [2] use sensor pattern noise as a clue for tracing back to the source camera. This method can distinguish cameras of the same model and brand.

The third approach is based on Color Filter Array (CFA) interpolation. Bayram et al [3] explore the CFA interpolation process to determine the correlation structure present in each color band which can be used for image identification. Long and Huang [4] obtain a coefficient matrix from a quadratic pixel correlation model where spatially periodic inter-pixel correlation follows a quadratic form. This coefficient matrix of each image is then fed into a neural network for classification in order to identify the source camera. In [5], Celiktutan et al use a set of Binary similarity measures, which are the metrics used for measuring the similarity between the bit-planes of an image. The underlying assumption is that proprietary CFA interpolation algorithm leaves correlations across adjacent bit-planes of an image that can be represented by these measures. 108 binary similarity measures are obtained for image classification purpose.

The fourth approach employs a set of image features for classifying source cameras. Kharrazi et al [6] identify a set of 34 features to be used for image classification; these features include RGB features, image quality metrics, and wavelet domain statistics.

In this paper, for the purpose of source cell phone identification, we modify and use the lateral chromatic aberration based method proposed for image forgery detection by Johnson and Farid [7]. Johnson and Farid use lateral chromatic aberration to detect image forgeries by estimating the chromatic aberration parameters of selected blocks on an image and compare them with the chromatic aberration parameters obtained for the whole image. Image tampering is then detected if inconsistency is found. In this work, we estimate the distortion parameters of the chromatic aberration of the image and use these extracted features to identify source cell phone through the use of SVM classifier. Our motivation arrives from two observations. Firstly, the aberration is more severe in camera phones whose lens system consists of low-end plastic materials instead of high-end, low dispersion aspherical lenses. Secondly, each camera model possesses a different lens structure thus it will experience somewhat different chromatic aberration. This difference can be expressed in terms of the distortion parameters.

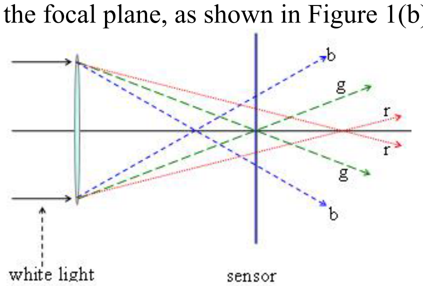
The remainder of this paper is organized as follows. In the next section, we introduce chromatic aberration and the proposed method to estimate the distortion parameters. In section 3, we perform several experiments on different cell phone models and provide the results. Section 4 gives some observations and discussions on the strengths and weakness of our method as well as the direction for future works. Section 5 concludes the paper.

2. CHROMATIC ABERRATION

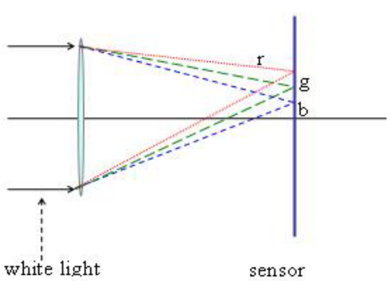
2.1. Background of Chromatic Aberration

In optics, dispersion is the phenomenon of lens having different refractive indexes for different wavelengths of light. Since the focal length of a lens is dependent on the refractive index, different wavelengths of light will be focused on different positions. This phenomenon is known as chromatic aberration, where lights of different wavelengths fail to converge to the same position on the focal plane (image sensor in a camera).

There are two kinds of chromatic aberrations [8]. Figure 1(a) shows *longitudinal* aberration where different wavelengths focus at different distances from the lens. *Lateral* aberration, on the other hand, is the phenomenon attributed to different wavelengths focusing at different positions on the focal plane, as shown in Figure 1(b).



(a) longitudinal aberration



(b) lateral aberration

Figure 1. Chromatic aberration.

To reduce chromatic aberration, camera designers combine convex and concave lenses of different refractive indices. Another technique is to use low dispersion materials such as fluorite to make low dispersion lenses.

Although both chromatic aberrations affect the images taken be the cameras, for simplicity we will concentrate only on lateral chromatic aberration in this paper.

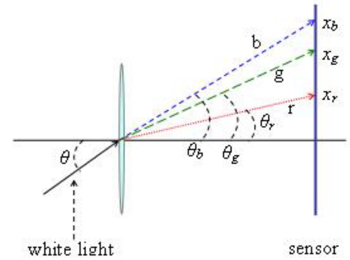


Figure 2. Modeling of lateral chromatic aberration.

According to Johnson and Farid [7], the relationship between the red ray and blue ray (in other words, the lateral chromatic aberration between red and blue wavelengths) as shown in Figure 2 can be modeled as $x_r \approx \alpha x_b$ where $\alpha = n_b / n_r$, n_b and n_r are the refractive index of the lens for blue and red wavelength respectively. In the case of 2D, we have a similar formula

$$(x_r, y_r) \approx \alpha(x_b, y_b) . \tag{1}$$

For a better model, we also need to take into account the centre of distortion (x_0, y_0), which is normally not the same as the centre of image. The model now becomes:

$$\begin{cases} x_r = \alpha(x_b - x_0) + x_0 \\ y_r = \alpha(y_b - y_0) + y_0 \end{cases} \tag{2}$$

2.2. Chromatic Aberration Estimation

Chromatic aberration causes misalignment between the RGB channels. Our task is to estimate the distorted parameters to compensate for the distortion. In this part, we will estimate the parameters (α_1, x_1, y_1) between the red and green channels and the parameters (α_2, x_2, y_2) between the blue and green channels. These six parameters then can be used as features for distinguishing source cell phones.

Let $R(x, y)$ and $G(x, y)$ be the red and green channel respectively. Then, the corrected red channel $R(x_r, y_r)$ is expressed as:

$$\begin{cases} x_r = \alpha_1(x - x_1) + x_1 \\ y_r = \alpha_1(y - y_1) + y_1 \end{cases} \tag{3}$$

The parameters (α_1, x_1, y_1) can be estimated by maximizing the mutual information between $R(x_r, y_r)$ and $G(x, y)$, which is computed as follows [7]:

$$I(R, G) = \sum_{r \in R} \sum_{g \in G} P(r, g) \log\left(\frac{P(r, g)}{P(r)P(g)}\right) \tag{4}$$

Where R and G are the random variables represent the values of the channels $R(x_r, y_r)$ and $G(x, y)$ respectively, $P(r, g)$ is the joint probability, and $P(r), P(g)$ are the marginal probability distributions. We maximize the mutual information using an iterative brute-force search as explained in section 2.3. The estimation for parameters

(α_2, x_2, y_2) between the blue and green channels follows a similar way.

2.3. Proposed Method

We maximize the mutual information using an iterative brute-force search. To ensure that the global maximum is found, the centers of distortion (x_1, y_1) and (x_2, y_2) are considered on the entire image. The value of α varies within the range [0.5, 1.5], which is determined empirically.

Searching over an entire image is very computational intensive; hence, sampling of the search space is used in each iteration to reduce computation. In each iteration, a distance δ of roughly 1/15 the size of the current search space is used as a sampling distance for jumping to the next centre of distortion. Searching the target α follows a similar fashion where in each round the sampling distance δ_α is taken to be 1/10 the length of current α-range. Once the point that gives maximum mutual information is found, the next iteration is started with a new search space around the maximum point with radius of δ and a finer sampling distance of $\delta/10$. Similarly, the new α-range is also limited to the area with a radius of δ_α around the new α, with the new sampling distance of $\delta_\alpha/10$. The process is repeated until δ=1 and δ_α is less than a predefined epsilon ε=0.0001. At the end of the execution, the parameters where the mutual information attains maximum value are returned.

The major execution time in each iteration is due to the interpolation to derive the values for $R(x_r, y_r)$ and the computation of the mutual information between $R(x_r, y_r)$ and $G(x, y)$. This time depends very much on the size of the channel under interpolation and mutual information computation. To reduce run time, only a small region on each image is used for calculation. In our implementation, we use a region of 100x100 pixels at the image centre for computing interpolation and mutual information. The accuracy rate remains the same but execution time drops dramatically, from 3 hours to 10 minutes per image on average. We also tried different positions (right top and bottom, left top and bottom) of 100x100 pixel region instead of at the image centre and the results are still comparable.

3. EXPERIMENTS AND RESULTS

3.1. Data Collection

We take 90 photos with each of the four cell phones (two Motorola V3i phones, one O2 XPhone II, and one Samsung Z140). The photos are taken with no zoom, using maximum resolution (Motorola's max resolution is 960x1280, others are 640x480). All pictures are in JPEG format.

The six parameters (α_1, x_1, y_1) and (α_2, x_2, y_2) are extracted for each of the taken images and used as features for image classification. One-third of the photos are fed into a Support Vector Machine (SVM) for training, another one-third is used for testing. To verify the effectiveness of our method in the case modification and cropping attack is used, we modify and crop one third of the taken images and use them to test the already trained model (initial training sequence remains the same). There are many SVM software tools available on the Internet, but we choose LIBSVM [12] for its simplicity. We use the provided script "*easy.py*" for running classification since its parameters are optimized.

3.2. Normal Classification

In the first experiment, we use the model to classify photos taken by three cell phones. The accuracy rate is high, with lowest rate of 86.67%, highest rate of 96.67% and the average rate of 92.22%. The confusion matrices are provided in Table 1.

		Predicted (%)		
		O2XII	Z140	V3i
Actual (%)	O2XphoneII	**86.67**	13.33	0
	SamsungZ140	3.33	**96.67**	0
	MotorolaV3i	6.67	0	**93.33**

Table 1. Classification of three cell phones.

3.3. Same Model Classification

In this experiment, we try to classify two cell phones of exactly the same model (Motorola V3i). The result is provided in Table 2. The accuracy of differentiating these two cameras is as low as 50%, which is not a practical number. This result shows that lateral chromatic aberration alone is not enough for identifying source cameras of the same model. Other forms of lens distortions may be additionally needed for a higher accuracy rate.

		Predicted (%)			
		O2XII	Z140	V3i#1	V3i#2
Actual (%)	O2XII	**86.67**	13.33	0	0
	Z140	3.33	**96.67**	0	0
	V3i#1	3.33	0	**50**	46.67
	V3i#2	6.67	0	36.67	**56.67**

Table 2. Classification of cell phones of the same model.

		Predicted (%)		
		O2XII	Z140	V3i
Actual (%)	O2XphoneII	**46.67**	46.67	6.67
	SamsungZ140	10	**76.67**	13.33
	MotorolaV3i	0	0	**100**

Table 3. Classification of modified images.

3.4. Modified Images Classification

Going a step further, we make some modifications to one-third of the taken images and use them for testing. The modifications include heavy JPEG compression, adding 5% Gaussian noise, and image sharpening. The confusion matrix is shown in Table 3. The accuracy for O2XphoneII is low (46.67%) while prediction rates for others remain high.

3.5. Cropped Images Classification

To see how well this method identifying source cell phone of cropped images, we perform the following experiment. For each of the 30 images from each camera phone, we randomly crop a region and extract the chromatic aberration parameters for the region then use them as features for image classification. The classification result is shown in Table 4. Although the accuracy is quite low for SamsungZ140, the result for other two camera phones is encouraging. It seems that the prediction accuracy depends very much on the target cell phones.

		Predicted (%)		
		O2XII	Z140	V3i
Actual (%)	O2XphoneII	**83.33**	10	6.67
	SamsungZ140	76.67	**20**	3.33
	MotorolaV3i	20	10	**70**

Table 4. Classification of cropped images.

4. DISCUSSIONS

When compared to the camera identification methods reviewed in section 1, this method has comparable performance to most of them, if not better than some of the methods. For instance, the method based on CFA interpolation [3] has prediction rate as low as 75% for one camera when classifying three cameras, whether our lowest rate is 86.67%. Similarly, the result in [5] is lower than ours when classifying some of the groups of three cameras, in particular, the lowest accuracy is only 71% compared to our lowest 87.67%. The paper [5] use different set of models of cell phones for experiments, however the results are comparable. Most of the methods suffer heavily from image modification attack. Our method also suffers from this, but the degree of suffering is not that severe (some camera model, like MotorolaV3i, can even have 100% prediction accuracy). Another point worth mentioning is that our method does not impose any restriction, while some of the listed methods have restrictions that sometimes not easy to achieve in practice (e.g. all cameras must take the same image contents with same resolution, etc).

As part of the future work, we plan to use longitudinal chromatic aberration as well for a better performance and higher reliability. Alternatively, we can also consider other ways of measuring chromatic aberration, such as the method using reference edges proposed by Willson and Shafer [10]. If optical zooming becomes a feature in mobile phones, the impact of optical zooming on source cell phone identification could be another area to be investigated. There have been several digital camera identification methods [11 – 13] proposed, which can be investigated for cell phone environment.

5. CONCLUSION

In this paper, we introduce a method for identifying source cell phone based on the footprints of lateral chromatic aberration left on images. By estimating the parameters of lateral chromatic aberration and use them as features for classification, we are able to identify the source cell phone of the given images with reasonably high accuracy. We also improve the runtime complexity of the lateral chromatic aberration based algorithm dramatically, by considering only a certain part of an image when estimating the parameters while preserving the accuracy at the same level.

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