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Image forgery localization using fine grained analysis of CFA artifacts

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Abstract: The usage of low-cost and high-resolution digital cameras and sophisticated photo editing software, digital images can be easily manipulated and altered. This project Image Forgery Localization using Fine-Grained Analysis of CFA Artifacts, a forensic tool, which able to discriminate between original and forged regions in an image captured by a digital camera. Most digital cameras employ a single sensor in conjunction with a color filter array (CFA). The assumption that the image is acquired using a Color Filter Array, and that tampering removes the artifacts due to the demosaicking algorithm. Then interpolate the missing color samples to obtain a three channel color image. This interpolation introduces specific correlations which are likely to be destroyed during tampering. This method is based on a new feature measuring the presence of demosaicking artifacts at a local level and on a new statistical model allowing deriving the tampering probability of each 2X2 image block without requiring a priori knowledge about the position of the forged region. Proposed method reduces error lavel to 19% and gives the Structural similarity of 98%.

Keywords: CFA artifacts, demosaicking, probability map, image tampering detection.

I. INTRODUCTION

An image is an array or matrix in which picture elements arranged in columns and rows. Pixel is the smallest element of an image. Each pixel store a value proportional to the light intensity at that particular location. Image processing is a method to convert an image into digital form and perform some operations on it. It is among rapidly growing technology today, with its applications in various aspects of a business. Image Processing forms core research area within engineering [10]

To categorize the image tampering based on different points of view generally, most often performed operations in image tampering are: deleting or hiding a region in the image, adding a new object into the image and misrepresenting the information of image. Here considering the traces left by the interpolation process. Image interpolation or demosaicking is the process of estimating values at new pixel locations by using known values at neighbouring locations. During the image life cycle, there are two main phases in which interpolation are applied:

Acquisition processing, to obtain the 3 colour channels (red, green, and blue)and the light is filtered by the Colour Filter Array (CFA) before reaching the sensor (CCD or CMOS), so that for each pixel only one particular colour is gathered, other two colours are interpolated and it is also used during transformations. Swaminathan in [2] exploit the inconsistencies among the estimated demosaicking parameters as proof of tampering. In [3] different demosaicking methods are discussed, it includes bilinear and bicubic, smooth hue transition, median filter, gradient based, adaptive color plane and threshold based variable number of gradients.

Generally speaking, demosaicking algorithms have several features in common. Missing colour values are determined from a weighted linear combination of neighbouring pixels, and the sum of the weights is one. As described in both [4] and [5], interpolation leaves a signature that can be reliably detected. Detailed analysis of the signal traces left by interpolation are found in [4] and [5]. Demosaicking can also be detected using methods which analyse generic resampling artifacts [6] and [7]. In this, the actual prediction weights of the resampling filter are not necessary for revealing periodic artifacts. Derivatives of interpolated images can be considered for window size at least 64x64 [8]. This paper includes another algorithm known as EM algorithm. EM stands for Expectation-maximization. The EM algorithm was explained and given its name in a classic 1977 paper by Arthur Dempster, Nan Laird, and Donald Rubin. It is an iterative method used to find maximum likelihood parameters of a statistical model in cases where the equations cannot be solved directly.

II. METHODOLOGY

Consider as specific CFA the most frequently used Bayers filter mosaic, a 2x2 array having red and green filters for one row and green and blue filters for the other. By focusing on the green channel, the even/odd positions (i.e.,acquired/interpolated samples) of the one-dimensional case turn into the lattice for the acquired green values and the complementary lattice for the interpolated green

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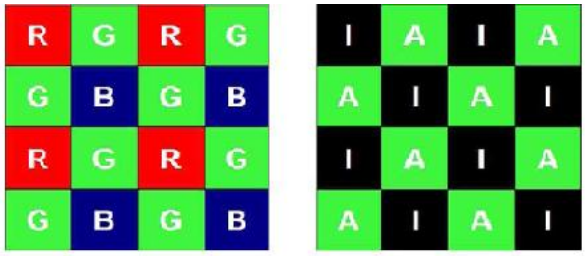
values. We assume that in the presence of CFA interpolation the variance of the prediction error on lattice A is higher than the variance of the prediction error on lattice I, and in both cases it is content dependent. On the contrary, when no demosaicking has been applied, the variance of the prediction error assumes similar values on the two lattices. Hence, in order to detect the presence/absence of demosaicking artifacts, it is possible to evaluate the imbalance between the variance of the prediction error in the two different lattices.



(a) (b)

Fig. 1 . (a) The Bayer's filter mosaic; (b) The lattice A for the acquired green channels and the complementary lattice B for the interpolated green channels.

Block diagram:

In system, given a suspected/forged image, produces the corresponding forgery map: each pixel in the forgery map indicates for each CxC image block its probability to contain CFA artifacts, so that low values in the output map correspond to likely forged areas. As a first step, the green channel is extracted from the image, and the prediction error is computed. Because in-camera processing algorithms are usually unknown, a fixed predictor is used. The weighted local variance is then estimated and the feature L (k, l) is obtained for each BxB block. The GMM parameters are globally estimated exploiting the EM algorithm and used for the generation of the forgery map. When C=B the forgery map is generated using the likelihood ratios in, whereas for C > B we use the cumulated likelihood map. Optionally, the intermediate log-likelihood map can be filtered using either a mean filter or a median filter.

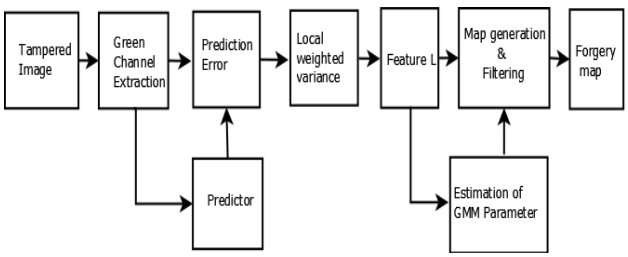


Fig. 2. Block diagram of proposed system

A. Green channel extraction

The green channel is extracted from the RGB image. Considering as specific CFA the most frequently used Bayers filter mosaic, a 2x2 array that contain red and green filter for one row and blue and green filter for another row(see fig (1). Then extract only green channel because the green channel is up sampled by a factor 2. Images can be stored as 3 array values, with each of the three values forming a single pixel. That is the colours are added together to form the final colour image. A pixel can be represented by I(x,y)(R,G,B). To extract green channel only use instruction that I(:,:,2), here 2 for green similarly 1 for red and 3 for blue.

B. Predictor

The image is filtered using a predictor kernel (Interpolation operation). The preditcted value is subtracted from the original green channel. Let us suppose that s(x,y) with (x,y)$\in z^2$ is an observed image. The prediction error can be obtained as:

$$\mathbf{e(x,y) = s(x,y)-\sum_{u,v\neq 0} kuv\, s(x+u, y+v)}$$

where $k_{u,v}$ is a bidimensional prediction filter. In the ideal case, $k_{u,v} = h_{u,v}$ $\forall$ (u,v) where $h_{u,v}$ is the interpolation kernel of the demosaicking algorithm. In general, we can assume that $k_{u,v} \neq h_{u,v}$ since the in-camera demosaicking algorithm is usually unknown.

C. Calculation of mean and variance

Statistical parameters of the acquired and interpolated pixels are computed that is mean and variance. According to the proposed model, the prediction error has zero mean and variance proportional to the variance of the acquired signal. However, when the prediction kernel is close to the interpolation kernel, the variance of prediction error will be much higher at the positions of the acquired pixels than at the positions of interpolated pixels.

$$\sigma_e^2(x,y)= \frac{1}{c}\ \left([\sum_{ij=-k} \alpha_{i,j} e^2(x+i, y+j)) - (\mu_e^2)\right]$$

where $\alpha_{i,j}$ are suitable weights.

$$\alpha_{i,j=} \begin{cases} w(i,j), \text{if } e(x+i,y+j) \text{ belongs to same class of } e(x,y) \\ 0\ , \qquad \text{otherwise} \end{cases}$$

W(i,j) is a (2k+1)x(2k+1) Gaussian window with standard deviation k/2

$$\alpha_{i,j=}\alpha'_{i,j/\sum}\alpha'_{i,j}$$

$$\mu_e=\sum \alpha_{i,j} e(x+i, y+j)$$

Where $c=1-\sum \alpha_{i,j}^2$

D. Mapping of variance

In this step we first separate acquired and interpolated pixels and calculate the mean and variance of each. The variance map is equal to the sum of Variance map of acquired plus the variance map of predicted pixels. Again the Geometric mean of the error variance for both the acquired and interpolated are calculated.

E. Defining the feature L

The proposed feature L allows us to evaluate the imbalance between the local variance of prediction errors

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when an image is demosaicked: indeed, in this case the local variance of the prediction error of acquired pixels is higher than that of interpolated pixels and thus the expected value of is a nonzero positive amount. On the other hand, if an image is not demosaicked, this difference between the variance of prediction errors of acquired and interpolated pixels disappears, since the content can be assumed to present locally the same statistical properties, and the expected value is zero. Let us now suppose that a demosaicked image has been tampered by introducing a new content, and that in order to make this forgery more realistic, some processing (blurring, shearing, rotation, compression, etc.) has been likely applied to the added content, thus destroying the demosaicking traces on the forged region. The proposed feature will assume in consistent values within the tampered image: in some regions (the untampered ones) it will be significantly greater than zero, while in other regions (the tampered ones) the feature will be close to zero . Let us now suppose that a demosaicked image has been tampered . We can thus employ these inconsistencies to nearly localize forgeries.

$$\mathbf{L(k,l)=\log \frac{GM_A(k,l)}{GM_I(k,l)}}$$

Where $\boldsymbol{GM_A\,(k,l)}$ is the geometric mean of the variance of prediction errors at acquired pixel positions and $\boldsymbol{GM_I(k,l)}$ similarly defined for the interpolated pixels.

$$\boldsymbol{GM_A\,(k,l)=\ [\prod \sigma_e^2(i,j)]^{1}/_{|B_{A_{k,l}}|}}$$

F. EM Algorithm

By using a Bayesian approach, for each block, it is possible to derive the probability that CFA artifacts are present/absent conditioned on the observed values of L(k,l). Let M1 and M2be the hypotheses of presence and absence of CFA artifacts respectively. In order to have a simple and tractable model, we assume that L(k,l) is Gaussian distributed under both hypotheses and for any possible size B of the blocks. If a demosaicked image contains some tampered regions in which CFA artifacts have been destroyed (as it may occur in a common splicing operation), both hypotheses M1 and M2are present, therefore L(k,l) can be modelled as a mixture of Gaussian distributions.

$$\mathbf{Pr(L(k,l)|}\boldsymbol{M_1}\mathbf{)=N(}\boldsymbol{\mu_1}\mathbf{,}\boldsymbol{\sigma_1^2}\mathbf{)}$$

When $\boldsymbol{\mu_1} > \mathbf{0}$

$$\mathbf{Pr(L(k,l)|}\boldsymbol{M_2}\mathbf{)=N(0,}\boldsymbol{\sigma_2^2}\mathbf{)}$$

The tampered regions in which CFA artifacts have been removed. In order to estimate simultaneously the parameters of the proposed Gaussian Mixture Model (GMM), we employ the Expectation Maximization (EM) algorithm. This is a standard iterative algorithm that estimates the mean and the variance of the component distributions by maximizing the expected value of a complete log-likelihood function with respect to the distribution parameters. Applying the equation to each block of an image, we obtain a likelihood map (LM), where each pixel of the map is the likelihood ratio associated to a B x B block. The tampered regions can be further highlighted by applying to the map a simple low-pass spatial filter, like a mean filter or a median filter.

For better numerical stability, such filters are applied to the logarithm of the likelihood map. In our case, the EM algorithm is used to estimate only $\boldsymbol{\mu_1}$, $\boldsymbol{\sigma_1}$ and $\boldsymbol{\sigma_2}$ since we assume $\boldsymbol{\mu_2 = 0}$. The final aim we point at is to achieve a map indicating for each B X B block $B_{k,l}$ its probability to be original/tampered based on its probability to contain or not CFA artifacts. Starting from and assuming a priori probabilities Pr(M1) = Pr(M2)= 1/2 we obtain the posterior probability of being an original block. By exploiting Bayer's Theorem and relying on the observed feature L (k,l) for each $B_{k,l}$ block we achieve:

$$\mathbf{Pr(}\boldsymbol{M_1}\mathbf{|L(k,l)=Pr(L(k,l)|}\boldsymbol{M_1}\mathbf{)\div\ (Pr(L(k,l)|}\boldsymbol{M_1}\mathbf{)\ +\ (Pr(L(k,l)|}\boldsymbol{M_2}\mathbf{))}$$

Which can be expressed as

$$\mathbf{Pr(}\boldsymbol{M_1}\mathbf{|L(k,l)=1\div(1+£(L(k,l)))}$$

Where £ is likelihood ratio of L(k,l)

III. RESULTS AND DISCUSSION

The result presented in this paper have been obtained on a dataset consisting of 5 original color images, in TIFF, JPEG format, coming from 4 different cameras (Canon EOS 450D, Nikon D50, Nikon D90, Nikon D7000).All cameras are equipped with a Bayer CFA, thus respecting our requirement that authentic images come from a camera leaving demosaicking traces, but the in-camera demosaicking algorithm of such devices are unknown.

Each image was cropped to 512 x 512 pixels, maintaining the original Bayer pattern, which is assume to be known. We will refer to such a dataset as the original dataset. Where a tampering is done by splicing a geometrically transformed image onto an image taken by a Nikon D90 camera. Fig 1 taken as original image and fig 2. Is the tampered image. Fig 5 here forgery map obtained using proposed algorithm.

Fig. 3. Original image

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Fig. 4. Tampered image (Image 1)

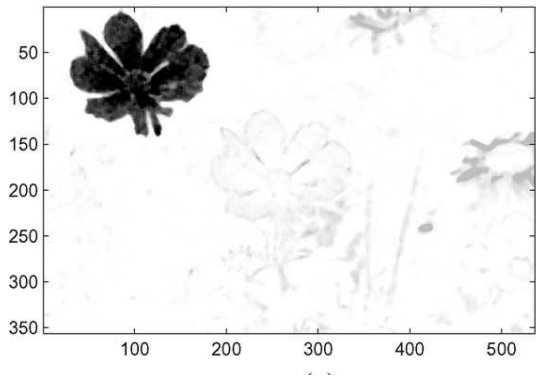

Fig. 5. Probability Map

Accuracy of the output can be determined by comparing the output image with reference image. Reference image can be obtained by subtracting the original image from input image. Complement of the output image must be taken for further calculation. By the mathematical operation

$$\frac{\text{Ref U Out} - \text{Ref} \cap \text{Out}}{\text{h} * \text{w}}$$

Where h and w are the dimension of the image. This is the direct indication of level of error that can be occurred in the proposed method. This paper also determines Structural Similarity Index Matching (SSIM). SSIM is used for measuring the similarity between two images. It is designed to improve on traditional methods such as peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human visual perception. SSIM can be calculated using equation

$$\textbf{SSIM (x,y)} = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

μ_x the average of x ;
μ_y the average of y ;
σ_x^2 the variance of x ;
σ_{xy} the covariance of x and y ;
$C_1 = (k_1 \text{L})^2$, $C_2 = (k_2 \text{L})^2$ two variables to stabilize the division with weak denominator;
L the dynamic range of the pixel values
k_1 =0.01 and k_2 = 0.03 by default.

These results are given in the following table.

TABLE I: EVALUTION OF PROPOSED SYSTEM

no	Results		
	Image	**error**	**Ssim**
1	Image 1	0.1287	0.9986
2	Image 2	0.1522	0.9974
3	Image 3	0.2428	0.9786
4	Image 4	0.2271	0.9729
5	Image 5	0.2228	0.9753

From this table, it is clear that structural similarity is high and the level of error is very low compared to the previous methods.

IV. CONCLUSION

In this paper, we focused main attention on the fine grained forgery localization problem. Here we have no prior knowledge about the tampered areas. We analyse artifacts left in the image by the interpolation process to reveal image forgery. In previous approaches for detecting forgeries either the area to be investigated has to be manually selected or also the automatic block processing but it results in poor detection performance. The result show that the proposed algorithm can be a valid tool for detecting and localizing forgeries in images acquired by a digital camera. Here, we define a new feature L to detect the presence or absence of forgeries. During tampering, the demosaicking artifacts are removed. The feature measures the CFA artifacts even at small 2x2 pixel level. The interpretation of absence of CFA artifacts is taken as an evidence of tampering. This paper includes measures to evaluate proposed system that are level of error and Structural similarity index matching. From the table it can be concluded that the error in proposed system is about 19% and Structural similarity is about 98%. Thus it is more efficient than the previous methods. Future work can be the study of segmentation algorithms that, by taking into account the local content characteristics allow to produce a final map with reduced false positives.

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