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LoG Feature Extraction Based Photographic Detection

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Abstract: ***Nowadays powerful digital image editing software makes image modification possible. There are many image processing and computer graphics techniques to manipulate images. This undetermines our trust in photographs. So a forgery detection method is proposed that uses inconsistencies in the color of illumination. This method is applicable to images containing two or more persons and no human interaction for tampering decision. For this, first compute the illuminant estimate of similar regions of the image. Then from the illuminant estimate textural and gradient features are extracted which are given to a machine learning approach for decision-making automatically. The illuminant color is estimated using a statistical gray world method and for extracting textural features, SASI is used. The gradient features are extracted using LoG feature extraction method. Log focuses on regions of high intensity change and it gives better result than any other feature extraction algorithms. These features are combined using a machine learning approach. For this, a SVM classifier is used. Thus photographic forgery can be detected.***

Keywords: illuminant color, LoG, SASI-descriptor, LoG-descriptor, machine learning, SVM classifier**.**

1. Introduction

Photographs play a vital role as they are powerful evidence and document in many fields. Today various photograph editing tools are available which undetermined the authenticity of photographs. So we proposed a technique to detect photographic forgery. Image splicing or composition of photographs is one of the most common type of image manipulation technique. In this, forgery is done by cutting a part of an image and pasting it in another image**.** Some processing is done on the copied part so that no one can figure out that some the image is tampered. **.** So a forgery detection method is proposed that uses inconsistencies in the color of illumination. This method is applicable to images containing two or more persons and no human interaction for tampering decision.

The input image is divided into regions of similar color called superpixels. A local illuminant estimator is computed over all superpixels. Recoloring all superpixels with its local illuminant estimator gives the illuminant map. The face extraction is done manually using bounding boxes. Then extract texture and gradient features of the face region from the illuminant map. For extracting texture features, use SASI and LoG. SASI can capture small granularities and discontinuities in the texture pattern. SASI is Statistical Analysis of Structural Information which defines a set of clique windows to extract and measure various structural properties of texture. SASI is based on statistics of clique autocorrelation coefficients, calculated over structuring windows. The SASI descriptor is based on second order statistics of clique autocorrelation coefficients over a set of moving windows. The clique windows of various size and shape used in SASI are used as a tool for defining the characteristics of textures in different granularity. Now gradient features are extracted using LoG algorithm. Laplacian of Gaussian is used to extract edge features. Laplacian filters are used to find areas of rapid change i.e. edges in images. Gaussian filtering is applied to smooth the image before applying Laplacian. This two-step process is called the Laplacian of Gaussian (LoG) operation. After that, pair all possible combinations of faces. Finally a machine learning approach is done automatically to classify the feature vectors. An image is a forged one if at least one pair of faces in the image is classified as inconsistently illuminated.

2. Related Works

Forgery detection based on Illumination-based methods is divided into either geometry-based or color-based methods. Geometry-based methods detect inconsistencies in light source positions between specific objects in the scene. Color-based methods detect inconsistencies in the interactions between object color and light color. Riess and Angelopoulou [1] use a method which uses a physics-based color constancy algorithm. It operates on partially specular pixels. In the image, regions having similar color are grouped to form superpixels and estimate the illuminant color locally per each superpixel. Recoloring each superpixel with its local illuminant estimate results in illuminant map .This cannot provide a numerical decision for tampering detection. Thus, an expert is required for the difficult task of examining an illuminant map visually for tampering detection. The disadvantage is that human visual system is not suitable for judging illumination. This is unable to detect inconsistencies in shadow, reflections etc. E.Kee and H. Farid [2] proposed a technique for measuring lighting conditions in an image.It is difficult to match the lighting conditions when creating a composite photograph of two or more persons. It describes how to measure lighting conditions in an image and describe its use in detecting photographic composites**.**It tells how to approximate a 3-D lighting environment with a low dimensional model and inconsistencies in lighting model are used as an evidence of tampering .The disadvantage is that it cannot be extended to arbitrary objects for which a 3-D model can be generated.

W. Fan, K. Wang, F. Cayre and Z. Xiong [3] proposed a 3-D lighting based image forgery detection using shape from shading method. This estimates 3D illumination using shape from shading. The advantage of this method is that 3D model of object is not required but reliability of algorithm is reduced. M.Johnson and H. Farid [4] proposed spliced image detection by exploiting specular highlights in the eyes. An inconsistency in shape of specular highlight on the eyes shows that the people were originally photographed under different lightening condition. The specular highlights that appear on eye are powerful cue to shape, color and location of light source. Inconsistencies in estimates from difference in shape and color of highlights are used to detect digital tampering. The problem is that this requires relatively a high resolution image of the eye. P. Saboia, T. Carvalho, and A. Rocha [5] proposed a method to derive more discriminative features for detecting traces of tampering in composite photographs of people. It uses powerful decision-making classifiers. It automatically classifies images by extracting additional features such as viewer position .It reduces classification error more than 20%.The disadvantages are people's eye must be visible and requires high resolution camera.

Tiago Jose de Carvalho, Elli Angelopoulou [6] proposed a method to detect forgery .The illuminant color is estimated by using a statistical gray edge method and a physics-based method which exploits the inverse intensity-chromaticity color space. It uses SASI [7] and HOG to extract illuminant features. Then gradient features are extracted using HOG edge. The extraction of edge points is done using canny edge detector and compute Histograms of Oriented Gradients (HOG) to describe the distribution of the selected edge points. To construct the feature vector, the histograms of all cells within a spatially larger region are combined and contrast-normalized. These features are combined using machine learning approach. The drawback is that the estimation of the illuminant color is error-prone and affected by the materials in the scene. Also it is not guaranteed to get accurate results. HOG has limitations that as the number of edges get after filtering is more it cannot detect forgery correctly in all cases.

3. Proposed System

The proposed system consist of six phases: Figure 1: shows flowchart of proposed method.

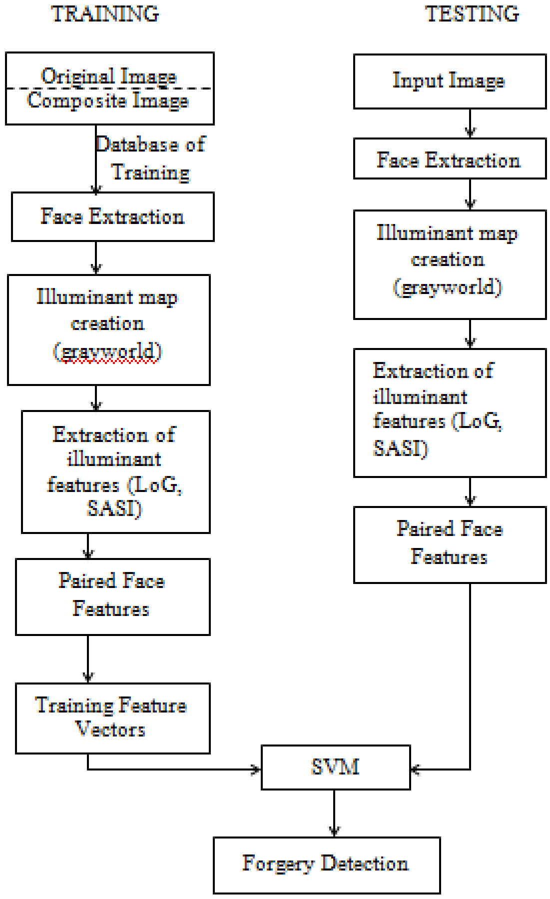

Figure 1: Flow Chart of Proposed Method

The six phases are

(1) Illuminant map creation: The input image is divided into regions of similar color. These regions are called superpixels. An illuminant color is estimated locally and replaced with each superpixel to form illuminant map.

(2) Face extraction: This is done manually using bounding boxes.

(3) Texture feature computation: Texture based features are extracted using Statistical Analysis of Structural Information algorithm (SASI).

(4) Gradient feature computation: Gradient based features is extracted using Laplacian of Gaussian algorithm (LoG).

(5) Paired feature creation: For an image consider all possible pairs of faces. For an image containing n_f faces ($n_f \geq 2$), number of face pairs is $(n_f(n_f-1))/2$.

(6) Classification: Classification is the process of classifying an unknown data to one of the predefined classes. This process consists of training and testing phases. To classify the images as genuine or forged SVM classifiers are used here.

The explanation of each of the section is given below.

3.1 Illuminant map creation

The input image is segmented into superpixels to compute local illuminant color estimates. i.e., regions of approximately constant chromaticity are achieved. For this we use Generalized Gray World Estimates. In this the average color of a scene is gray. So if there is a deviation of the average of the image intensities from the expected gray color, it is due to the illuminant. An extension of this idea by van de Weijer *et al.* [8] is used in the generalized gray world approach.

Let $f(x) = (f_R(x), f_G(x), f_B(x))^T$ denote the observed RGB color of a pixel at location. Van de Weijer *et al.* [8] consider purely diffuse reflection and linear camera response. Then f(x) is formed by

$$f(x)=\int_{\Omega} e(\lambda,x)s(\lambda,x)c(\lambda)d\lambda \quad (1)$$

where Ω is the spectrum of visible light, λ is the wavelength of the light, e(λ,x) is the spectrum of the illuminant, s(λ,x) is the surface reflectance of an object, and c(λ) is the color sensitivities of the camera i.e., one function per color channel. Van de Weijer *et al.* [8] extended the original gray world hypothesis which is the incorporation of three parameters:

- Derivative order: the assumption that the average of the illuminants is achromatic which can be extended to the absolute value of the sum of the derivatives of the image.
- Minkowski norm: greater robustness can be achieved by computing the p-th Minkowski norm of these values instead of simply adding intensities or derivatives
- Gaussian smoothing: smooth the image with a Gaussian kernel of standard deviation to reduce image noise.

Van de Weijer *et al.* proposed a method to estimate the color of the illuminant by putting all these three aspects together as

$$ke^{n,p,\sigma} = \left(\int \left| \frac{\partial^n f^\sigma(x)}{\partial x^n} \right|^p dx\right)^{\frac{1}{p}} \quad (2)$$

where x denotes a particular position i.e. pixel coordinate ,k denotes a scaling factor, $|.|$ denotes the absolute value, ∂ is the differential operator, $f^\sigma(x)$ is the observed intensities at position , smoothed with a Gaussian kernel σ and the integral is computed over all pixels in the image. The 'e' is computed for each of the color channel separately. The advantage of using derivative operator is that it increases the robustness against homogeneously colored regions of varying sizes and for the Minkowski norm is that it exploits specular edges better as it emphasizes strong derivatives over weaker derivatives. Here the Gray world illuminant maps are computed by setting n=1,p=1 and σ =3.

3.2 Face extraction

This is done manually by setting a bounding box around all faces in an image. The advantage of using a human operator is that it minimizes false detections or missed faces and scene context is important when judging the lighting situation.

3.3 Texture feature computation

Textural features are computed from illuminant map using Statistical Analysis of Structural Information (SASI) algorithm. It is based on statistics of clique autocorrelation coefficients, calculated over structuring windows. SASI defines a set of clique windows to extract and measure various structural properties of texture. The advantage of using SASI is its capability of capturing small granularities and discontinuities in texture patterns.

The SASI descriptor is based on second order statistics of clique autocorrelation coefficients over a set of moving windows. The clique windows are of various size and shape. The clique windows are defined by a neighbourhood system, which is a tool for describing the characteristics of textures in different granularity. The structure of the clique windows controls the order of the neighbourhood system. SASI is used with a broad class of textures, which may consist of discontinuities or small primitives due to the flexibility in the definition of clique windows. Distinct illuminant colors interact differently with the underlying surfaces; as a result it generates distinct illumination texture.

The SASI descriptor measures the structural properties of textures which is based on the autocorrelation of horizontal, vertical and diagonal pixel lines over an image at different scales. It considers only a small number of shifts. The autocorrelation functions are not computed for every possible shift. Using a specific fixed orientation, scale, and shift, one autocorrelation is computed. Then compute the mean and standard deviation of all such pixel values to get two feature dimensions. Repeat this computation for varying orientations, scales and shifts to get a 128-dimensional feature vector. This vector is normalized by subtracting its mean value, and dividing it by its standard deviation. Please refer to for further details [9]. The SASI descriptor is calculated over the Y channel from the YC_bC_r color space.

The advantage of using SASI is that capability of capturing small granularities and discontinuities in texture patterns.The SASI is more successful than the Gabor Filter descriptors as it captures small granularities and discontinuities such as sharp corners and abrupt changes. SASI has higher average retrieval rates than Gabor Filter descriptors due to the flexibility in designing the clique windows. But the main disadvantage of SASI descriptor is its high computational complexity.

3.4 Gradient feature computation

Gradient based features are extracted using Laplacian of Gaussian algorithm (LoG) [10]. Edges in an image correspond to object boundaries. They are pixels where image brightness changes sharply. Information of an edge is given by using the relationship of a pixel with its neighbourhoods. Many of them are implemented with convolution mask and based on discrete approximations to differential operators. The rate of change in the image brightness function is measured by these differential operations.

Laplacian filters are derivative filters used to find areas of rapid change i.e. edges in images. We have to smooth the image using a Gaussian filter before applying the Laplacian in order to reduce its sensitivity to noise. This two-step process is called the Laplacian of Gaussian (LoG) operation. Its input is a single gray level image and produces another gray level image as output. The LoG operator takes the second derivative of an image. The LoG-descriptor is calculated over the Y channel from the YC_bC_r color space.

The Laplacian of an image focus on regions of rapid intensity change and so they are used for edge detection. We have to find a discrete convolution kernel which approximates the second derivatives in the definition of the Laplacian as the input image is represented as a set of discrete pixels. As these kernels are approximating a second derivative measurement on the image, they are very sensitive to noise. In order to overcome this, the image is Gaussian Smoothed before applying the Laplacian filter. This pre-processing step reduces the high frequency noise components.

The advantage of using this two-step process is that as both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations. The Laplacian of Gaussian kernel can be pre-calculated in advance so only one convolution needs to be performed at run-time on the image.The Gaussian smoothing operator is used to `blur' images and remove noises.

The advantage of using this LoG is that it finds the correct places of edges and test wider area around the pixel. The disadvantage is that malfunctioning can occur at the corners, curves and where the gray level intensity function varies. It cannot find the orientation of edge because of using the Laplacian filter. This is advantageous compared to canny in the sense that canny requires complex computations, time consuming and more computational expense.

3.5 Paired feature creation

We have to consider all possible pairs of faces. .For an image containing nf faces ($n_f \geq 2$), number of face pairs is (n_f (n_f-1))/2.To compare two faces, we combine the same descriptors for each of the two faces. For example, we can concatenate the SASI-descriptors that were computed on gray world or The LoG-descriptors that were computed using grey world. The conclusion is that feature concatenation from two faces is different when one of the faces is an original and one is spliced.

The SASI and LoG-descriptors capture two different properties of the face regions. SASI and LoG, in combination with the gray world illuminant maps create features which will discriminate well between original and tampered images. The descriptor for all possible pairs of faces are compared separately and if there is any difference between the descriptors, we conclude that the image is forged otherwise the image is original.

3.6 Classification

Classification is the process of assigning an unknown data to one of the predefined classes. A classifier is used by means of data with known classes. The two phases of this process are training phase and testing phase. In the training phase, the system is learning to find a mapping between the features extracted from the images in the training set and their classes. In the testing phase, the system uses this learned model and the features extracted from new images in the testing phase are assigned to one of the classes. Here we use a SVM classifiers are used to classify the images as genuine or forged.

A Support Vector Machine (SVM) classifier defines a hyperplane that separates the data into two different classes. SVM also provide good generalization in high dimensional inputs and determine the decision boundaries in the training step. SVM classification is based on the concept of decision planes that define decision boundaries. SVM classifier supports both binary and multiclass targets. Here we use binary classifier as the output is either original or forged.

We classify the illumination for each pair of faces in an image as either consistent or inconsistent. The information provided by the SASI features is complementary to the information from the LoG features. Thus, we use a machine learning-based fusion technique for detection. SASI or LoG features on gray world are classified using a support vector machine (SVM) classifier. We classify each combination of illuminant map and feature type independently i.e., SASI-Gray-World, Log-Gray-World by using a two-class SVM classifier to obtain the distance between the image's feature vectors and the classifier decision boundary. Finally we get the output of SVM classifier as the image is either original or forged.

4. Experimental results

The proposed algorithm is evaluated by considering two datasets. One dataset consists of images that we captured ourselves and the second one contains images collected from the internet.

- DSO-1: This is the dataset created by ourselves and the first dataset. It consists of 100 indoor and outdoor images. 50 images are original, i.e., have no modification and 50 are forged in this set of images. The forgeries were created by adding one or more individuals in a source image that already contained one or more persons. Some color and brightness adjustments are done in order to increase photorealism.
- DSI-1: This is our second dataset and it is composed of 50 images (25 original and 25 doctored) downloaded from different websites in the Internet with different resolutions.

The Figure 2: is a forged image. Using SASI-Gray-World and Log-Gray-World we get the result as forged image. Sometimes SASI cannot detect images correctly. In that case also, LoG correctly detects whether it is a forged image or original.

Figure 2: Forged image

For the forged image shown in Figure 2, both SASI and LoG detects it as a forged image as shown in Figure 3 :(SASI output) and Figure 4: (LoG output).

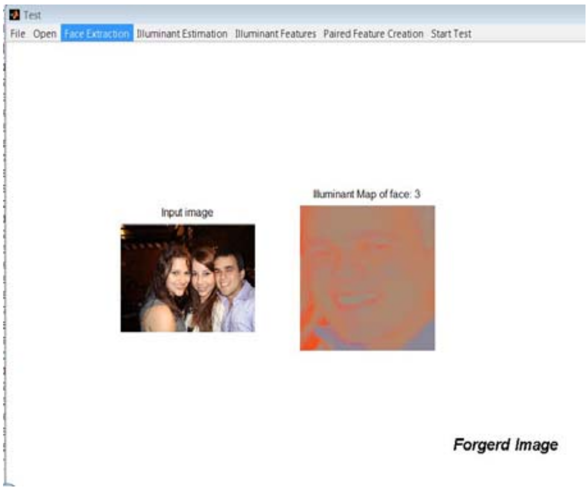

Figure 3: SASI output

Here the SASI correctly detects the image as forged image. The LoG feature extraction also detects it as forged image.

Figure 4: LoG output

Figure 5: original image

But the image showed in Figure 5: which is an original image, SASI detects it as a forged image. In this case the LoG correctly detects it as an original image. So we get better results by using LoG feature extraction method. The SASI output for the above image is shown in Figure 6.

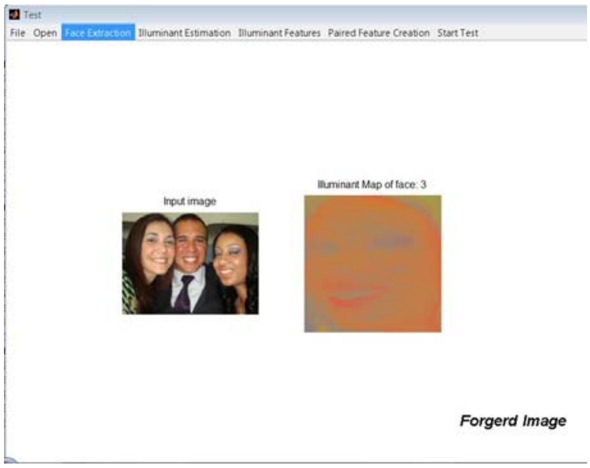

Figure 6: output of SASI

The LoG output for Fig.5 is shown below in Fig.7 which is the correct output.

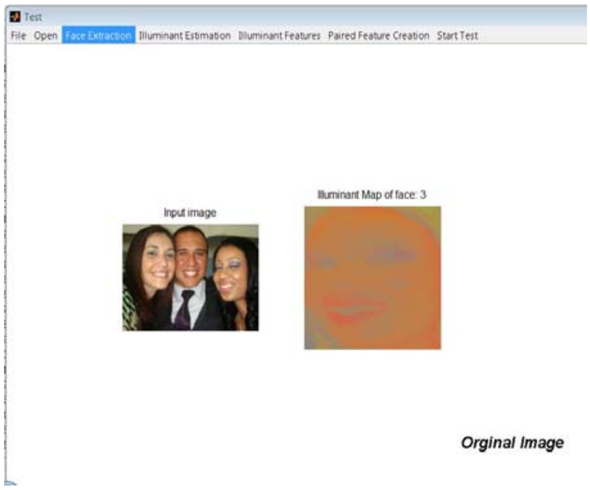

Figure 7: LoG output

Compared to any other feature extraction methods, LoG feature extraction method gives the correct and accurate results. So even if, other algorithm fails to give correct result, LoG gives the required correct output.

5. Conclusion

The methods which are used to solve the problem of verifying the authenticity of a digital image are increased rapidly in the recent years. So we presented a new method for detecting forged images of people using the illuminant color. The illuminant color is estimated using a statistical gray world method .We extract texture and gradient information separately from these illuminant maps. The edge information is described using LoG feature extraction method and texture features by SASI algorithm. We combine these descriptors using machine learning called SVM classifier. SVM classifier is used extensively and obtained good performance. There are training phase and testing phase. The features like texture and gradient are extracted using training phase. SVM classifier is trained and used to classify the query image as genuine or forged .This method serves as an intelligent system for detecting the images as either original or tampered.

6. Future Scope

The possible future studies include detection of forged person in the image whereas in the proposed method we can only detect whether the image is forged or not. We can use other feature extraction techniques such as SFTA (Segmentation-based Fractal Texture Analysis) to get the features. Also we can do the face extraction automatically rather than manually. If more advanced illuminant color estimators become available, then further improvements can be achieved as the use of illuminant color is error prone.

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