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Digital Image Forgery detection using color Illumination and Decision Tree Classification

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Abstract –
As an image can convey more information than words, many people rely on them for communication. To establish the authenticity that the image is not a composite or spliced image, this paper proposes a new technique that detects the image forgery based on illuminant color estimation. The proposed system estimates illuminant color of the image and creates illuminant maps of human faces in images using Gray world approach and IIC space. It then extracts the texture features of the faces by using an integrated technique which incorporates Gabor local binary pattern for which Histogram of Orientation are derived by HOG Edge algorithm. SASI descriptor is used to calculate the distance in statistical information of the paired faces. The proposed system needs human interaction only to select the human faces on images. As the existing forgery detection methods rely on human experts to take final decision on tampering, this paper includes a classification using decision tree classifier which works by machine learning and eliminates the need for human expert to take final tampering decision. The results of decision tree classifier are potential to indicate the authenticity of images.
Key words – Authenticity, illuminant color, Gray world approach, IIC, Gabor local binary pattern, HOG Edge algorithm, SASI descriptor, machine learning.

I. INTRODUCTION

Images are popular means of communication and many people rely on them, so it is necessary that their authenticity should be proved. As the field of image processing and its applications has grown and extended to large area, there is an increase in the availability of image editing software also. Due to the easy availability of digital editing tools, alteration, and manipulation became very easy and as a result forgery detection becomes a complex and threatening problem. Because of this, a large number of doctored or edited images are circulating in our media of communication. This can deceive the viewer, and forces him to accept or agree on the contents of the image.

Fig.1. Is this image an authentic one? An example spliced image involving multiple human faces.

Images can be a source of evidence in different areas of our daily life applications. In a courtroom, an image can be an evidence of a murder, or any civil or criminal investigation. Images undergo scrutiny test to verify its authenticity. So it is necessary to verify the trustworthiness of the images.

Splicing or image composition is a type of forgery that can create a single composite image of people from two or more images[2]. The above figure Fig.1 is an example in which the man in the middle is an inserted one. The splicing is one among the harmful image manipulation technique.

Based on the fact that no two images taken for splicing have same lighting conditions, the illuminant extract of the image can be used for splicing detection; i.e, the amount of light incident on the faces chosen from different images to create a composite image is not the same. Though editing the image content is easy, it is difficult or highly impossible to adjust the illuminant conditions comparable to other image taken for splicing. Most of the image editors does not concentrate or notice the difference in image illuminancy. Therefore the illuminant estimates of the image can be a powerful tool in forensic analysis of splicing detection.

Reiss and Angelopoulo[3] proposed that illuminant estimates from local image regions can be analyzed by human experts to detect the illumination inconsistencies. This is very challenging, as most of the illumination features eludes the human visual system.

To minimize or to fully eliminate the need of human experts in digital image forgery detection, the system should be automated [1]. The introduction of a classification scheme that functions based on machine learning can accomplish this task. The classification scheme categorizes the images into two families: consistent and inconsistent based on the estimated illuminant conditions and texture – cum – edge features.

The important contributions of this paper are summarized as follows:

1) Creating illuminant maps of images.
2) Introducing an integrated approach of feature extraction (texture –cum- edge features).
3) Minimizing human interaction in tampering decision making.
4) Semi – automated Forgery detection.

In Section II, related works that make use of illuminant features are discussed. In Section III, the development of illuminant maps for images using statistical and physics – based methods are discussed. The algorithms used in the proposed method are discussed in Section IV. Some results of the experiments on different database images are in Section V. The conclusions and the future work are outlined in Section VI.

II. RELATED WORKS

These image forgery detection approaches can be divided into two categories: 1) active and 2) passive-blind. The active approach may focus on data hiding (e.g. watermarking, steganography) and digital signatures which is based on prior information about the image [2]. On the other hand, the passive approach on image forgery detection does not require any prior information of image to be investigated. It is based on the fact that editing the image content may result in uneven distribution of image features. (e.g. statistical changes).

The forgery detection techniques that are based on illuminant estimation can fall on two categories: 1) geometry – based and 2) color based. Geometry based methods focus on inconsistencies in lighting whereas color based methods describes how chromaticity of an object varies with different intensities of light [4] – [9].

It was Johnson and Farid[4] who proposed that illuminant inconsistencies can be used for splicing detection. Kee and Farid [5] extended this approach to analyze the 3-D surface geometry of the objects in the image. Johnson and Farid [7] also showed that by simplifying some assumptions made on estimating lighting conditions, the complex lighting environment can be approximated and represented in low dimensional model. Then the parameters of the low dimensional model can be estimated and used in detecting the inconsistencies in lighting. It relies on acquiring multiple images of the same scene as the complex light source direction identification is very difficult using a single image.

Johnson and Farid[9] and Saboia *et al.*[11] proposed image splicing forgery detection using the specular highlights on the eye of the people in images. These methods have limited application as it requires that eyes of the people should be clearly visible.

Another method for splicing forgery on images involving reflective surfaces on scene was proposed by O'Brien and Farid[8]. It is based on the assumption that reflective surface is flat and linear projection. It has limited application and ineffective when the reflective surface is curved.

Riess and Angelopoulo [3] proposed a new approach for color constancy. It is a physics – based color constancy algorithm that exploits the inverse intensity – chromaticity color space. It segments the image regions and estimates the dominant illuminant color for each region. They did not provided the results of illuminant estimates to an objective algorithm. So the analyses of extracted illuminant features are left to human experts. Manual analysis on illuminant features is more error prone and time consuming. This is a drawback of this method.

Later Carvalho *et al*[1] extended the work of Riess and Angelopoulo by incorporating machine learning based SVM classifier to take final tampering decision. It combined the statistical and physics – based illuminant estimation schemes. It also extracts the texture features which can be given as input to the classifier.

In this paper, we build upon the ideas of [1] ,[18], and [19]. Rich illuminant features are extracted and decision on illuminant color and texture estimates are given to an objective classification based on decision tree classifier makes the paper distinct from the prior works.

III. COLOR CONSTANCY AND ILLUMINANT MAPS

In image forensic analysis, the investigators make use of all known evidences of tampering detection like shadows, reflection, replicated blocks, steganalysis etc. In the viewpoint of image manipulator, it is very tedious or nearly impossible to alter the illuminant conditions of individual photographs that are taken to create a composite image. So illuminanat estimation can be used as a forensic tool [2].

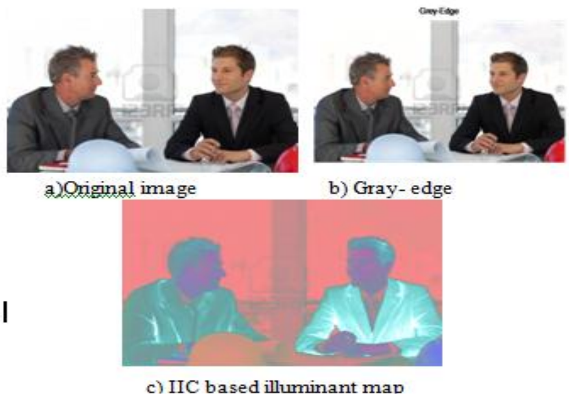

Fig.2 Example illuminant maps for a original image – Gray edge and IIC based illuminant estimates.

Detecting that the image has undergone some editing operations after the image is caught is some what difficult by the human visual system. Most of the image editing operations can elude our vision and it is unable to visualize them with our human eye. So illuminant maps (IM) that estimates the color constancy can be developed and used for analysis. Therefore, illuminant maps are the intermediate representation of the color constancy that can be taken for investigation in forensic analysis.

Most of the color constancy algorithms are based on the assumption on specularities of the image contents. The color constancy algorithms discussed in [12] – [15] proves that each algorithm has its own advantages in different mode of applications. These algorithms can fall on two categories: statistics based and physics – based. Statistics based algorithms are based on some crisp assumptions. Gray world, Max – RGB are few among them. Physics – based algorithms focus on interaction of intensity and color of the image contents.

Gray – edge color constancy [15] is one of the new and effective approaches on color constancy. It integrates other statistical based algorithms like Gray – world and Max –RGB with Minkowski norm. Physics – based color constancy[like IIC [3] exploits the RGB image into a YCbCr color space as it represents the interaction of illuminant intensity with the color of the object.

The example image with its illuminant map derived from Grey – edge illuminant estimation is shown in Fig.2. The color of the pixels in the image is equalized so that an additional color due to multiple illuminant sources is removed. The IIC illuminant map is obtained in YCbCr color space.

However, illuminant estimation is error prone and is affected by the scene content. There are also many challenges in analyzing the illuminant maps as discussed in [1]. On analyzing the illuminant of face regions, the pigmentation of the skin color also affect the illuminant estimation. But these errors are relatively small compared to other materials that are present in the image scene. Manual analysis of the illuminant maps that are obtained can itself provide forgery detection. But implementing them in machine learning approach reduces the human expert need.

IV. OVERVIEW AND ALGORITHMIC DETAILS

The proposed method of forgery detection can be organized into five main components.

1) *Local Illuminant Estimation(IE):* The input image is segmented into homogeneous blocks and illuminant maps are derived from the Gray – edge and IIC.
2) *Interactive Face Extraction:* This is the only step that requires human interaction in the proposed system. The operation in this step is to set a bounding box around the faces in the image.
3) *Extraction of Illuminant Features:* For all the face regions texture and edge gradients are computed on the illuminant maps.
4) *Distance Measure of paired faces:* This step computes the differences in the mean values of texture and edge features.
5) *Classification:* A machine learning approach that automatically classifies the feature values to check whether the illuminant conditions of the faces under investigation are consistent or not.

Fig. 3 shows the architectural design of the proposed system.

A. LOCAL ILLUMINANT ESTIMATION

To compute the illuminant color estimates two separate illuminant estimators (IE) are used: gray world estimator and physics based illuminant estimator called inverse intensity – chromaticity space. The resulting intermediate representation of the illuminants is called illuminant map (IM). Both the illuminant maps are then independently analyzed.

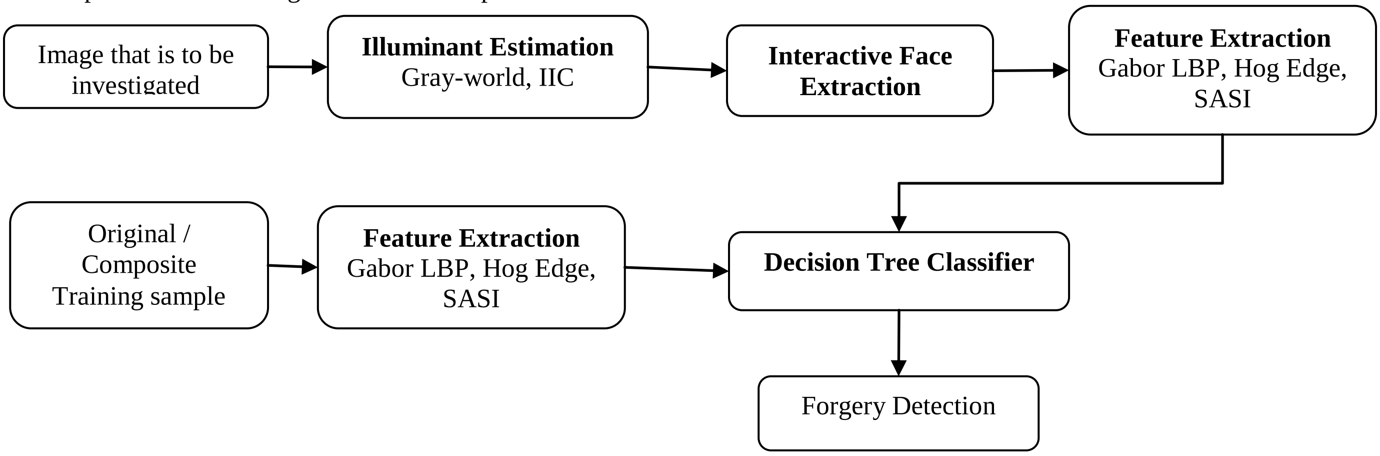

Fig. 3 Architectural Design of the proposed system

1) Gray – edge Illuminant Estimates:

The gray world assumption [12] states that the average color of the image scene is gray. Any deviation from the average value of the intensity of image is due to the illuminant. Initially, the image color is equalized to 0.5 i.e. gray. Maximum color (Max – RGB) [13] for each channel is then estimated.

$$R_{\max} = \frac{R}{R+G+B}, G_{\max} = \frac{G}{R+G+B}, B_{\max} = \frac{B}{R+G+B} \quad (1)$$

With these two estimates, grey – edge features [15] are estimated. The formula used to estimate the color of the illuminant *e* is

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

In the above equation, the integral is calculated over all pixels in the image, where *x* is the pixel coordinate, *k* represents the scaling factor. Derivative order *n*, Minkowski norm p, Gaussian smoothing *σ* to reduce the image noise are the other factors.

2) Inverse Intensity – Chromaticity space Illuminant estimates:

The image intensities estimated are assumed to have a mixture of diffuse and specular reflectance. Pure specularities consist of only the illuminant color. First the RGB color space is converted to YCbCr color space as it represents the intensity and chromaticity parameters. The intensity $I_c(x)$ is modeled as

$$I_c(x) = \int (e(\lambda, x)s(\lambda, x) + e(\lambda, x))c(\lambda)d\lambda \quad (3)$$

where *e* represents the gray world illuminant estimate, *s* is the specular reflectance value, *c* is the color channel, *c ε* {R,G,B} at position *x*.

The chromaticity component $\chi_c(x)$ is computed as

$$\chi_c(x) = m(x)\frac{1}{\sum_{i \in \{R,G,B\}} f_i(x)} + \gamma_c \quad (4)$$

where *m(x)* is the light position, surface orientation and camera position. *m(x)* cannot be computed, some constant value is assigned.

B. INTERACTIVE FACE EXTRACTION

This is the only phase which needs human interaction. The system requires bounding boxes around all faces in the image. There are different automated algorithms available that can be used to generate the bounding boxes. However, human operators are preferred to select the face regions in this system for two main reasons:

1) It minimizes missing faces and false detections.
2) The scene context is very important in judging the lighting condition. Automated algorithm is less effective in this point of view.

C. EXTRACTION OF ILLUMINANT FEATURES

The texture features are extracted by Gabor local binary pattern [19]. HOG features are calculated by taking orientation histograms of edge intensity in local region. A HOG feature vector represents local shape of an object, having edge information at plural cells. Statistical Analysis of Structural Information (SASI) is used for the extraction and proved that the SASI is a kind of distance measure of the mean values of the texture maps.

1) Gabor Local Binary Pattern (Gabor LBP)

In this approach [19], a face image is modeled as a “histogram sequence”. It works by dividing a facial image into small regions and compute the description of each region using local binary patterns. These descriptors are used to derive a spatially enhanced histogram or feature vector.

2) Interpretation of Illuminant Edges : HOG Edge algorithm

Given the face region from an illuminant map, extract the edge points using Canny edge detector [20], which yields a large number of spatially close edge points. Then compute Histograms of Oriented Gradients (HOG) [16] for each edge points, which describes the distribution of edge points. HOG output is used as the feature vector that can be used for the next stage i.e. Classification.

3) Texture Description – SASI Algorithm

Statistical Analysis of Structural Information (SASI) [17] is used to extract the texture information from the illuminant maps. It also measures the structural properties of textures based on autocorrelation of horizontal, vertical and diagonal pixel lines of image. Then compute the mean and standard deviation of all pixel values.

D. Classification

Decision Tree (DT) Classifier [19] is a simple and widely used classification technique. The main objective of decision tree classifiers is to classify correctly as much of the training sample as possible; The SASI features of the image that are derived from previous step are given as input to the classifier. It adopts a learning algorithm to identify the model that best fits the attribute set and class label of the input data. Therefore, the key objective of the learning algorithm is to build predictive model that accurately predict the class labels of previously unknown records. The distance measure of the texture values are used for final forgery detection.

IV. EXPERIMENTS AND RESULTS

The experiment is done on the images in the dataset. The dataset contains the original images and also spliced images that were generated using Photoshop image editing software. The illuminant estimates are determined using gray world, max – RGB, gray edge and IIC space. The illuminant extract itself can provide a clue to detect the forgeries by a human expert on analyzing the illuminant feature in detail. The faces are cropped from the IIC image.

Fig. 4 Example Images in the dataset and their extracted faces (a) Original Image (b) Spliced image with the middle person inserted.

Generally in forensic analysis, there will be no reference original images. To understand that there will be changes, an example dataset image is spliced and analyzed. The illuminant estimates for the faces of the image in original image are same and the value is 2089 in Fig.4. The illuminant estimates of the faces in the spliced image are: 5028.07, 5467.39 and 2268 respectively. It indicates that the third face is a spliced one.

The experiments show that there is a great difference in the illuminant estimates of the images when they are spliced. This is because, while editing the image, the manipulator performs different functions to make the image look more like original one. This can alter the edge features of the image. The difference in the illuminant estimates of the first two faces of the spliced image is less but there is a large difference with that of third face.

V. CONCLUSION AND FUTURE WORK

In this paper, a new method for detecting forged images of people using the illuminant color estimates is proposed. Two separate illuminant estimators are used: gray world estimator and physics based illuminant estimator called inverse intensity – chromaticity space. The illuminant maps are treated as texture maps. The edge information is also extracted. In order to describe the texture –cum-edge patterns, an integrative algorithm based on Gabor local binary pattern, HOG edge descriptor and SASI descriptor is proposed. These complementary cues are used in machine learning based classification.

Though the proposed system is developed to detect the splicing on images containing multiple faces, it can also be used to detect splicing done on other scene objects. The proposed system requires only a minimum human interaction in forgery detection. User interaction is needed only to select the bounding boxes of the human faces on the image. The final decision on image forgery is automated to eliminate the need for a human expert to take tampering decision.

The illuminant estimate can be a powerful forensic tool; however it is prone to estimation errors. Further improvements can be achieved when advanced color constancy algorithms are used for illuminant estimation. This is the subject of future work.

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