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RESULT PAPER ON DIGITAL IMAGE FORGERIES BY ILLUMINATION COLOR CLASSIFICATION

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Abstract: Nowadays image modification is easy due to availability of powerful digital image editing software and distributed by newspaper, magazine, website, television. In all these information channel images are powerful tool for communication .Digital content is widespread and also redistribute either lawfully or unlawfully. After images are posted on internet, other users can copy resize and re-encode them and then repost their version by generating similar but not identical copies. It is difficult to adjust the illumination condition when Image composition or splicing operation performed on image to create composite image. Due to these illumination inconsistencies give clue to detect forgery. But method that operate on illuminant color affected by material in the scene , so improvement can be achieved by advanced illuminant estimator as skin color of the faces automatically detected in the image. Skin colors provide enough and reliable information to estimate the scene illuminant. Physics and statistical based illuminant estimators are applied on image. For all face region texture and gradient based feature are extracted and provided to machine learning approach for automated decision making. Image is forgery if at least one pair of face is classified as inconsistently illuminated. Also another method include which can identify, relationship within faces of image is shown by Image Phylogeny Tree (IPT) which is constructed by calculating distance feature of faces from image. The technique is applicable to image containing two or more people.

Keywords: Color constancy, Forgery detection, Illuminant color, Image composition or splicing, Image Phylogeny Tree.

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INTRODUCTION

Past few years have seen a considerable rise in the availability and sophistication of digital imaging technology (cameras, scanners, software) and their use in manipulating digital images. **I**mages are posted on the Internet, other users can copy perform some transformation on them and then repost their versions. Images are distributed by different information channel such as newspaper, magazines, websites and television. Due to availability of powerful tool we can easily manipulate image by using image processing techniques. Images which are posted generating similar copies but not identical, due to which illegal contents are spread over internet to identify such duplicate images problem, researchers give name it as NDDR(Near Duplicate Detection and Recognition) It has several application such as

1) Security: To reduce illegal version of images find out the suspect information.

2) Forensics: If analysis is performed on original image better result obtained.

3) Copyright Enforcement: to analyze image recovery, its history in case the image leaks onto the Internet, potentially having multiple variations.

By considering the concept of biological evolutionary process with analogy, we generate a tree named as Image Phylogeny Tree(IPT) to find out the history of transformation that generate this image to show the relationship between near duplicate image but the main task is to find out original image between near duplicate images. Image composition (or splicing) is one of the most common image manipulation operation. Image contain faces are automatically detected by Partial Least Square analysis proposed by Scharwtzet al.[16] Illuminant Map is constructed by dividing the image into homogeneous region and each region is colored with extracted illuminant color. Features are computed based on texture and radiant based and form joint feature vector consisting of all possible pair of faces. An image as a forgery if at least one pair of faces in the image is classified as inconsistently illuminated but method that operated on illuminant color are prone to estimation error, it can be further improved by using advanced illuminant estimator as skin color information using a rough skin detector.

2. Literature Review & Related work

Forgery detection method based on illumination are either geometry based or color based .In geometry based ,more focus is on inconsistencies between light source position [1]-[5] between objects whereas in color based focus is on inconsistencies between light color and object color [8],[9]. Johnson and Farid [2] describe lightening based forensic technique for detection of forgery image. The main idea behind that it is difficult to adjust lightening condition, It is more appropriate in single lightning environment, but less in more complex lightning environment. Inconsistencies in the lighting model are then used as evidence of tampering. After that Kee and Farid [3] extended this approach for 3D lighting environment, with knowledge of 3-D

surface normal, the direction to the light source can be estimated. In the case of faces, a dense grid of 3-D normal improves the estimate of the illumination direction. 3D surface normal cannot be determined from single image for that they considered 2- D surface normal at occluding boundaries. It removes all the ambiguities from in 2D lightening technique. Gholap and Bora [6] introduced method based on illumination color estimation cues to image forensics and proposed a method to find the forgery in digital images by exploiting color mismatches among the objects in the image. Fan *et al.* [4] used shape-from-shading technique and for the description lightening environment 3D surface normal is used. The notion behind these are various mismatches introduced in image during creation of composite image. Limitation is additionally specularities present on all region of interest in real world image to overcome this limitation Wu and Fang assumes [9] purely diffuse reflectance and use proper illuminant estimator. Due to splicing operation inconsistencies are introduce .Color inconsistencies which are introduced are use for forgery detection in which image is divide into block Dichromatic reflectance model is used to show inconsistencies in specularities. Specularity segmentation on real world images is challenging [9]..Illuminant color is estimated from each block and difference between illuminant color is measured if greater than threshold then block is labeled as splice block. But limitation of this method is it requires manual selection of manual "reference block". A visual system might achieve color constancy by a variety of means and it is useful to classify approaches into color invariant, or illuminant estimation procedures. In illuminant estimation procedures, color constancy is achieved by first obtaining an estimate of the illuminant in a scene from the image data recorded for that scene. The phenomenon of color constancy: how a visual system is able to ensure that the colors it perceives remain stable, regardless of the prevailing illumination, has received considerable attention in the context of both human and computer vision. Once the scene illuminant is known, the recorded image data is corrected to discount the color of the scene light and thus render the image color constant. Color invariant approaches on the other hand, achieve constancy without explicitly estimating the scene. Gijsenij [9] presented methodology that enables color constancy under multiple light sources. Ebner [8] presented an approach to multi-illuminant Estimation but in practice oversmooths the illuminant boundaries. The methodology is designed according to the following criteria:

1) It should be able to deal with scenes containingmultiple light sources;

2) it should work on a single image;

3) No human intervention is required; and

4) no prior knowledge or restrictions on the spectral distributions of the light sources is required. Although the proposed framework is designed to handle multiple light.

3. Analysis

In Existing Heng Yao et.al.[11] identify the forensic object in the photography. Our aim is to determine whether two objects in an image have proper relationship in size satisfying the perspective rules.Therefore, we only need to find the ratio of the objects' heights, rather than calculate their absolute heights, which are hard to get since the camera height is generally unavailable.

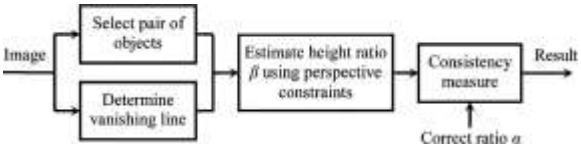


Fig. 1. Existing Method proposed in [11]

Fig. 1. Existing Method proposed in [11] To remove drawback of existing method we compare objects in an image with illuminant feature. The input image is subdivided into homogeneous region of similar color .an illuminant color is locally estimated using pixel within each superpixel Recoloring each superpixel with it's local illuminant color estimator gives an intermediate representation called Illuminant Map. It is difficult to argue based on illuminant map that given image is manipulated or normal because estimation of illuminant color is error prone and affected by material in the scene. Hence We need advanced illuminant color estimator as skin color particular to faces which provide reliable information to form scene illuminant estimator. The notion behind this is the light penetrates into the body of material where it is scattered and selectively absorbed that form the characteristic of material. The body reflection provides characteristic of object color. Skin composed of thin layer epidermis and dermis which is thick layer. Epidermis has the property of optical filter. In dermis light is absorbed and scattered [10]. Pigmentation is the most effective skin characteristics but it depends upon many factor. However the intra-material variation is smaller than estimation error occurring due to material in scene. Evolution of near duplicate images which are gone through transformation is described by an Image Phylogeny tree. That Requires the prior knowledge of the set of near duplicates, and also a dissimilarity function d that computes small values for similar images, and large values for distinct images, those that have suffered more significant transformations. Let $T\theta$ be the transformation from a family T then dissimilarity function between two images IA and IB is given as

$$d\,IA, IB = |\,IB - T\theta(IA)\,| \quad (1)$$

When IA and IB have different dimensions, d IA, IB would calculate the image metric of the residual on IB's image dimensions, while d IB, IA would calculate the image metric of the residual on IA's image dimensions. There are two important factor while constructing image phylogeny tree from set of near duplicate image; dissimilarity function and tree building

algorithm. There are some possible image transformations an image can undergo to produce near duplicate of itself.

• Quality transformations (like blur, noise, reencoding, and change of brightness or contrast).

•Postproduction transformations (like cropping, insertion of text or logos, picture in picture, and background replacement).

4. Challenges in the exploiting illuminant map

The input image is subdivided into homogeneous region of similar color .an illuminant color is locally estimated using pixel within each super pixel. Re-coloring each super pixel with its local illuminant color estimator gives an intermediate representation called Illuminant Map. Consider example Fig 1 shows image and its illuminant map in which inconsistencies can be directly observe: All fruits in scene have transition from red to blue except orange in the top right have multiple green spots which is inserted in image In Fig.1 however, it is difficult to justify the Image is doctored or not directly hence experts concentrate on more reliable region such as faces. It is also challenging to argue, based on these illuminant maps, that the right-most girl in the bottom image has been inserted, while, The illuminant maps are created with the IIC-based illuminant Estimator. most boy in the top image is original. To avoid such human decision pattern recognition scheme operated on illuminant map is use.

Fig. 2. Example illuminant map that directly shows an inconsistency.

But the estimation of illuminant color is error prone and affected by material in the scene. The body reflection provides characteristic of object color. Skin composed of thin layer epidermis and dermis which is thick layer. Epidermis has the property of optical filter. In dermis light is absorbed and scattered [14]. Hence we need advanced illuminant color estimator as skin color which provides reliable information to form scene illuminant estimator particular to faces. Pigmentation is the most effective skin characteristics but it depends upon many factors [15]. However the intra-arterial variation is smaller than estimation error occurring due to material in scene.

5. Methodology And Obeservation

5.1 Methods Used

The proposed system used SVM classifier to classify image as forensic or normal. Static and physics based color constancy algorithm are used to extract illuminant feature. Inconsistencies regarding texture and gradient based are computed using Statistical Analysis of Structural Information (SASI) and Histogram Oriented Gradient algorithm

5.1.1 HOG edge algorithm (Histogram Oriented Gradient algorithm)

Dissimilar illuminant estimates can occur for a number of reasons: changing geometry, changing material, noise, retouching or changes in the incident light.

- To characterize such edges canny edge detection algorithm is used.
- When an image is spliced, the statistics of these edges is likely to differ from original images.
- Characterize such edge discontinuities, Feature descriptor called HOG edge algorithm is used.

5.1.2 SASI (Statistical Analysis of Structural Information)

We use the Statistical Analysis of Structural Information (SASI) descriptor by Carkacioglu and Yarman-Vural [19] to extract texture information from illuminant maps. Recently, Penatti *et al.* [20] pointed out that SASI performs remarkably well.. Distinct illuminant colors interact differently with the underlying surfaces, thus generating distinct illumination “texture”. This can be a very fine texture, whose subtleties are best captured by SASI. For our application, the most important advantage of SASI is its capability of capturing small granularities and discontinuities in texture patterns .SASI is a generic descriptor that measures the structural properties of textures. It is based on the autocorrelation of horizontal, vertical and diagonal pixel lines over an image at different scales. Instead of computing the autocorrelation for every possible shift, only a small number of shifts is considered. As a final step, this vector is normalized by subtracting its mean value, and dividing it by its standard deviation. .

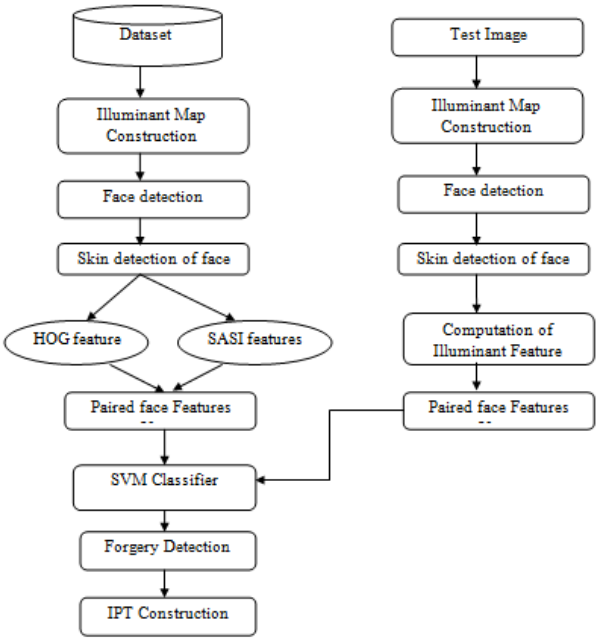


Figure 3 Flow of proposed work

6.Praposed Methode

6.1Illuminant Map Construction

The input image is segmented into homogeneous region and color of illuminant is estimate, each region is recolor with extraction of illuminant color and give Illuminant Map(IM),. Here two illuminant maps are obtained using separate color estimator as an extension of statistical generalized gray world by Weijer romaticity space proposed by Tan et al. [18].

6.2 Face Detection

Faces are extracted from an images represented by bounding boxes around all faces in an image.

6.3 Skin Detection

Illuminant color estimator prone to estimation error and affected by illuminant material in the scene. Hence we limit our detector to skin and in particular to faces . Hence

6.4 Computation of Illuminant Feature

Texture and gradient based feature are extracted from IM for all face region. Statistical Analysis of Structural Information (SASI) feature are calculated over Y channel from YCbCr color space. HOG edge also applied on Y channel from YCbCr color space on skin of extracted faces.

6.5 Paired Face Features

Same descriptor for each of two faces is compare because feature concatenation from two faces is different when one face is original and one is spliced. If image contain *nf* faces then number of face pair is(*nf* (*nf* -1))/2 .mainly the focus is on to assess whether pair of face in image is consistently illuminated. The SASI and Hogedge descriptors capture two different properties of the face regions. Joint feature vector are formed such as SASI with generalized gray world, SASI with IIC , Hogedge with generalized gray world, Hogedge with IIC.

6.6 Classification

Image classified as forgery if at least one pair is inconsistently illuminated**.** Machine learning approach is used to classify the feature vector .Individual feature vector SASI or Hogedge with gray world or IIC based illuminant map are classified using Support vector machine (SVM) classifier. Fusion technique is used because The information provided by the SASI features is complementary to the information from the Hogedge features .Thus, machine learning-based fusion technique for improving the detection performance is used.

6.7 IPT Construction

Image phylogeny tree is constructed using segmented faces extracted from image.

7. RESULT AND DISCUSSION

7.1 Illuminant Map Construction

Input Image which is to be detected whether it is normal or forensic is select then apply illuminant estimatorm algorithm and apply illuminant conversion ecause Hogedge calculation and SASI descriptor perform on Y

channel of YCbCr so we get an Illuminant Map as shown in figure 4.

Fig. 4 (a)Input image (b)Illuminant Map

7.2 Face Detection

Faces are extracted from an image

Fig. 5 Face Detection

7.3 Skin Detection

Skin color of each face is detected by using skin detector

7.4 Computation of Illuminant Feature

Texture based feature are extracted using SASI algorithm to check inconsistencies in texture pattern in accordance with contrast, scaling and periodicity. Gradient based feature are extracted using HOG algorithm, apply on each faces extracted from image.

Fig. 6(a)Face with skin detection(b) result of Canny edge detector

7.5 Paired Face Feature

Metafusion technique is used to form joint feature vector because features which are extracted using SASI and HOG are complementary to each other. Feature vector is

given as input to SVM classifier.

12	13	14	15	16	17	18	19
0.3063	0.2876	0.2594	0.3494	0.3520	0.4647	0.2680	0.3191

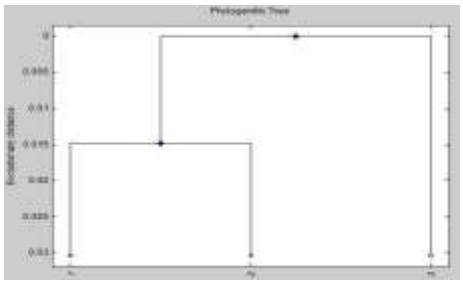
7.6 Classification

Image is classified as forgery if at least one pair is inconsistently illuminated.

Fig. 7 Message box for normal image and Forensic Image

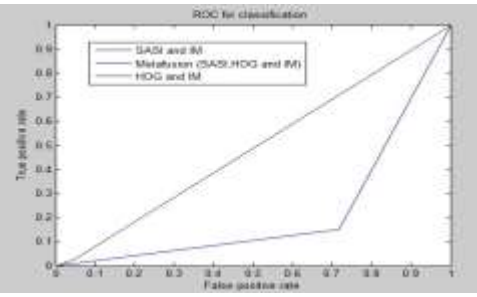
7.7 IPT Construction

Image Phylogeny tree is constructed using segmented faces from image according to their feature characteristic as shown in figure 9



I have taken 104 no. of image as dataset which contain 52 original images and 52 composite image collected from internet. Here Sensitivity represents the no. of composite images are correctly classified and specificity represents number of original images correctly classified.

After result analysis I have got accuracy of 76.9% images are correctly classified by Metafusion and nearly about 50% by individual SASI ,IM and HOG , IM.



8. Conclusion And Future Scope

In this Project, machine learning approach is used to exposed image as normal or manipulated .Illuminant color is estimated by using statistical generalized gray edge method and physics – based method as inverse intensity chromaticity color space , join feature are extracted based on texture and gradient from Illuminant Map for all face region . SASI and Hog edge algorithm are complementary to each other hence to form join feature vector late fusion technique named SVM – Meta fusion is used. We consider an image as a forgery if at least one pair of faces in the image is classified as inconsistently illuminated. Advanced illuminant estimator as skin color of faces is incorporated due to challenges in exploiting Illuminant Map and method that operate on illuminant color prone to estimation error, yield good result. As there is no need of Camera Parameter because forgery is detected by comparing illuminant feature of faces from image, hence problem with existing method is solved. In proposed System forgery is detected by comparing illuminant feature of faces from image .Illuminant feature are extracted from skin color which provides reliable information to form scene illuminant estimator. As skin detection approach is used to detect forgery so that It will helpful to detect pornography compositions which, according to forensic practitioners, have become increasingly common nowadays. In this project Image phylogeny tree is constructed by using segmented faces extracted from image. My future work is to construct IPT to show the relationship between n near duplicate images which are created by performing set of transformation on image and post new version of image on internet .We detect original image by proposed method after that we construct IPT for n near duplicate images to know the history of image evolution

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