ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 4) Pages (122-135)
IJREB
Journal home page: www.ijreb.org

ROBUST DIGITAL IMAGE FORGERY DETECTION BASED ON SPARSE CLASSIFIER

Lisa Samuel[1] and J.Benita[2]

[1]PG Student, Dept. of ECE, Noorul Islam University, Kumaracoil, Tamil Nadu

[2]Asst Professor, Dept. of ECE, Noorul Islam University, Kumaracoil, Tamil Nadu

ABSTRACT

Every day, millions of digital documents are produced by a variety of devices and distributed by newspapers, magazines, websites and television. In all these information channels, images are a powerful tool for communication. Unfortunately, it is easy to use computer graphics and image processing techniques to manipulate images. The digitally forged images are sometimes so real and it cannot be distinguishable from the original image. However, before thinking of taking appropriate actions upon a questionable image, one must be able to detect that an image has been altered or not. Image composition and splicing are the most common image manipulation operations. A forgery detection method is used which exploits subtle inconsistencies in the color of the illumination of images. The sparse classifier is used to identify the forged image. This approach is machine learning based and requires less user interaction. This method incorporates information from physics and statistical based illuminant estimators on image regions of similar material. Since the sparse classifier is having good performance in the classification process, the forgery detection method helps to identify the digitally modified images with high accuracy.

KEYWORDS: Illuminant color, image forensics, machine learning, spliced image detection, texture and edge descriptors.

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

INTRODUCTION

Day by day millions of digital documents are produced by a variety of devices and distributed by Medias like television, magazines, newspapers and websites. In all these information channels, images are a powerful tool for communication. Unfortunately, it is not difficult to use computer graphics and image processing techniques to manipulate images. Photographic manipulation raises a host of legal and ethical questions that must be addressed. However, before thinking of taking appropriate actions upon a questionable image, one must be able to detect that an image has been altered or not. Image composition and splicing are the most common image manipulation operations. Fig.1 shows an example of an original image and a forged image. When assessing the authenticity of an image, forensic investigators use all available sources of tampering evidence. Among other telltale signs, illumination inconsistencies are potentially effective for splicing detection, from the view point of a manipulator, proper adjustment of the illumination conditions is hard to achieve when creating a composite image.

Fig: 1 Example of an original image and a fake image

Images, unlike text, represent an effective and natural communication media for humans, due to their immediacy and the easy way to understand the image content. Historically and traditionally, there has been confidence in the integrity of visual data, like a picture printed in a newspaper is commonly accepted as a certification of the truthfulness of the news and video surveillance recordings are proposed as probationary material in front of a court of law.

With rapid diffusion of inexpensive and easy to use devices that enable the acquisition of visual data, almost everybody has the possibility of recording, storing, and sharing a large amount of digital images. At the same time, the large availability of image editing software tools makes extremely simple to alter the content of the images, or to create new ones, so that the possibility of tampering and counterfeiting visual content is no more restricted to experts. Finally, current software's

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

create photorealistic computer graphics that are indistinguishable from photographic images and also generate hybrid generated visual content. Today a visual digital object might go during its lifetime, from its acquisition to its fruition, through several processing stages, aimed at enhancing the quality, creating new content by mixing pre existing material, or even tampering with the content. As a consequence of all previous facts, doctored images are appearing with a growing frequency in different application fields, and thus today's digital technology has begun to erode the trust on visual content, so that apparently "seeing is no longer believing". All these issues will get worse as processing tools become more and more sophisticated.

The situation highlights the need for methods that allow the reconstruction of the history of a digital image in order to verify its truthfulness and assess its quality. Two questions about the history and credibility of an image can be raised: Was the image acquired by the device it is claimed to be sensed with? Is the image still depicting the captured original scene? The first question is of major interest when the knowledge of which is the source of the image represents the evidence itself, for example, since it allows to know the user or device that made the picture; the second question has more general interest. Answering to those queries is relatively easy when the original image is known. In practical cases, almost no information can be assumed to be known a priori about the original image. Investigators need, therefore, to authenticate the image history in a blind way.

IMAGE FORGERY

The trustworthiness of photographs has an essential role in many areas, including: forensic investigation, criminal investigation, surveillance systems, intelligence services, medical imaging, and journalism. The art of making image fakery has a long history. But, in today's digital age, it is possible to easily change the information represented by an image without leaving any obvious traces of tampering. Despite this, no system yet exists which accomplishes effectively and accurately the image tampering detection task.

There are many different reasons for modifying an image: The objective could be, to improve its quality or to change its semantic content. In some cases, the processed image will carry the same information as the original one, but in a more usable or pleasant way.

ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 4) Pages (122-135)
IJREB
Journal home page: www.ijreb.org

Hence, this kind of editing is referred as "innocent." Conversely, in other cases, the semantic information conveyed by the image is changed, usually by adding or hiding something. Thus this kind of editing is treated as "malicious." Image forgery means creating an image by altering its content.Duping the recipient into believing that the objects in an image are something else from what they really are. One such example is shown in Fig 1. The image itself is not altered, and if examined will be proven as so. This method is where the context of the image is altered.

Image forgery is classified into two categories. The first class of image forgeries includes images tampered by copying one area in an image and pasting it onto another area. It is called as Copy-Move Forgery or Splicing. The second class of forgeries is copying and pasting areas from one or more images and pasting on to an image being forged. The image processing community formally refers to this type of image as an image "composition," which is defined as the "digitally manipulated combination of at least two source images to produce an integrated result". It is also called as Copy-Create Image Forgery.

Image splicing is a simple process of cropping and pasting regions from the same or different images to form another image without post-processing such as edge smoothing. Image splicing is one of the simple and commonly used image tampering schemes. Since splicing is often used.

Fig: 2 An altered and its original authentic image

Image tampering as an initial step, and splicing itself, with modern image processing techniques, can often hardly be caught by the human visual system, image splicing detection is of fundamental importance in image tampering detection. Image composition is commonly used in forgery making process, which is created by taking an object from one image and pasting it into another one. Post-processing such as image smoothing and noise addition is often involved. The detection of image composite blindly is of much challenge and importance because the involved post processing is complex.

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

Image forensics aims to address image authenticity and integrity. Image tampering, splicing or cloning has been done to create forged images. Therefore the integrity of the image is lost. The digitally forged images are sometimes so real and it cannot be distinguishable from the original image, hence authenticity is also lost. Integrity and authenticity verification of digital images are one of the hot and serious research issue in the field of image processing.

SCOPE OF THE PROJECT

Whenever digital images are understood as a means to convey information, it is important to ensure the trust worthiness of this information. In particular the image has to be authentic, ie, the image has not been manipulated and the depicted scene is a valid representation of the real world. Often, it is not only the depicted scene that is considered to convey information, but also the image's origin and the circumstances that led to the respective image.

Hence, judging about the trustworthiness of a digital image means to infer the history of that particular image. In general, the question of trustworthiness is connected to the question who operated the devices involved in the image generation process. It will restrict the considerations on the origin of an image to the determination of the actual devices: The image itself cannot reveal the identity of the device operator. So image forensics is used to detect forgeries.

The images and data of financial, legal evidences, medical reports, such assets originality and authenticity is of prime importance. Identifying the originality and authenticity of image or data in many cases becomes challenging problem. The advance in computer graphics, animation, multimedia in association of high computing machines, algorithms, increases the complexity of the issue. It is possible to generate high precision realistic images and data of any events. Identifying and differentiating the data and image acquired by acquisition devices and realistic computer generated one is a multidimensional problem that has drawn attention of researchers worldwide. 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. Specific to image forgery detection image can be manipulated in various ways with

IJREB

International Journal of Research in
Engineering and Bioscience
ISSN 2321-743X
Volume 2 (Issue 4) Pages (122-135)
Journal home page: www.ijreb.org

many simple operations like affine transforms (such as translation, scaling, rotation, shearing) compensation operations (like color, brightness, contrast adjustments, blurring and enhancement) and suppression operation (such as filtering, compression and noise addition). Additionally more complex operations are also possible such as compositing, blending, matting, cropping, photomontage leading to visually untraceable artifacts in an image. The automatic and scientific method of detecting the forged images has become a biggest challenging problem to researchers and the same problem is true for every multimedia contents.

RELATED WORK

Christian Riess and Elli Angelopoulou [1] propose illumination color as a new indicator for the assessment of image authenticity. Many images exhibit a combination of multiple illuminants (ash photography, mixture of indoor and outdoor lighting, etc.).Here the user selects illuminated areas for further investigation. a physics-based method for the recovery of the illuminant color for different objects in the scene is used. However, is somewhat limited by the it's less accuracy, and complex algorithms. An efficient approach, describe a technique for exposing such fakes by detecting inconsistencies in lighting is proposed by Micah K. Johnson, and Hany Farid [2]. When creating a digital forgery from multiple images, it is often difficult to exactly match the lighting conditions. This approach is limited due to less sensitive, difficult to exactly match the lighting etc.

Eric Kee, Hany Farid [3] has proposed a system with knowledge of 3-D surface normals, the direction to the light source can be estimated. Because 3-D surface normals usually cannot be determined from a single image, only the 2-D surface normals at occluding boundaries were considered. In return, only two of the three components of the light source direction were estimated. To achieve this, a 3-D face model is registered with the 2-D image using manually annotated facial landmarks.Fan *et a*l. [10] propose a method for estimating 3-D illumination using shape from shading. In contrast to [9], 3-D model of the object is not required. However, this flexibility comes at the expense of a reduced reliability of the algorithm.

Xuemin Wu, Zhen Fang [4] proposed method in which illuminant color inconsistency

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

is used to detect image splicing. This system introduces a new approach to detect image splicing and locate splicing area by exploiting illuminant color inconsistencies. The illuminant color is estimated based on image blocks. Then the estimation error of each block is calculated by comparing the estimates with the reference illuminant color. But it requires manual selection of reference block and the algorithm is not applicable to indoor images.

Priscila Saboia, Tiago Carvalho, and Anderson Rocha [5] presented that the specular highlights that appear on the eye are a powerful cue to the shape, color, and location of the light source in the scene. Inconsistencies in these light properties can be used as telltales for detecting tampering. But the limitations are high resolution image is needed, low detection rate and the peoples eye must be visible.

Arjan Gijsenij, Rui Lu, and Theo Gevers [6], addressed more realistic scenarios where the uniform light-source assumption is too restrictive. Quantitative and qualitative experiments on spectral and real images show this methodology reduces the influence of two light sources simultaneously present in one scene.

Simone Bianco Raimondo Schettini [7] investigate how illuminant estimation can be performed exploiting the color statistics extracted from the faces automatically detected in the image. This method is based on two observations: first, skin colors tend to form a cluster in the color space, making it a cue to estimate the illuminant in the scene; second, many photographic images are portraits or contain people.The proposed method can be directly used in many digital still camera processing pipelines with an embedded face detector working on gray level images.

Joost van de Weijer, Theo Gevers, and Arjan Gijsenijthis [8] propose a new hypothesis for color constancy namely the gray-edge hypothesis, which assumes that the average edge difference in a scene is achromatic. Based on this hypothesis, they propose an algorithm for color constancy. The experiments show that the proposed color constancy algorithms obtain comparable results as the state-of-the-art color constancy methods with the merit of being computationally more efficient. The work by Bleier et al. [19] informs that on smaller image regions many off-the-shelf single-illuminant algorithms do not scale well.

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

SYSTEM ARCHITECTURE

The proposed method consists of five main components:

1) *Dense Local Illuminant Estimation (IE):* The input image is preprocessed, then it is segmented into homogeneous regions. An illuminant map with gray world image and inverse intensity chromaticity is obtained.

2) *Face Extraction:* This is the only step that may require human interaction. The face is cropped manually and extract both SASI features and HOG edge features.

3) *Computation of Illuminant Features:* for all face regions, texture-based and gradient-based features are computed on the illuminant map values. Each one of them encodes complementary information for classification.

4) *Paired Face Features:* The aim is to assess whether a pair of faces in an image is consistently illuminated. For an image with faces, construct joint feature vectors, consisting of all possible pairs of faces.

5) *Classification:* Classification is a process in which individual items (objects/patterns/image regions/pixels) are grouped based on the similarity between the item and the description of the group. A machine learning method is used to automatically the features. The image forgery is considered if at least one pair of faces in the image is classified as inconsistently illuminated. Fig 3. Shows the architecture of the proposed work.

A. Dense Local Illuminant Estimation

To compute a set of localized illuminant color estimates, the input image is preprocessed using coherence filter, then segmented into superpixels, i.e., regions of approximately constant chromaticity, using the algorithm by Felzenszwalb and Huttenlocher [14]. Per superpixel, the color of the illuminant is estimated. Here two separate illuminant color estimators are used: the statistical generalized gray world estimates and the physics-based inverse-intensity chromaticity space. Obtain two illuminant maps by recoloring each superpixel with the estimated illuminant chromaticities of each one of the estimators. Both illuminant maps are independently analyzed in the subsequent steps.

1) Generalized Gray World Estimates: The classical gray world assumption by Buchsbaum [15] states that the average color of a scene is

ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 4) Pages (122-135)
IJREB
Journal home page: www.ijreb.org

gray. Thus, a deviation of the average of the image intensities from the expected gray color is due to the illuminant. Compared to the original gray world algorithm, the derivative operator increases the robustness against homogeneously colored regions of varying sizes.

2) Inverse Intensity-Chromaticity Estimates: The second illuminant estimator consider in this paper is the so-called inverse intensity-chromaticity (IIC) space. It was originally proposed by Tan *et al.* [14]. In contrast to the previous approach, the observed image intensities are assumed to exhibit a mixture of diffuse and specular reflectance. Pure specularities are assumed to consist of only the color of the illuminant. In practice, these constraints are straightforward to compute. The pixel colors of a patch are projected onto IIC space. Principal component analysis on the distribution of the patch-pixels in IIC space yields two eigenvalues λ_1,λ_2 and their associated eigenvectors v_1 and v_2 . Let λ_1 be the larger eigenvalue. Then v_1 is the principal axis of the pixel distribution in IIC space. In the two-dimensional IIC-space, the principal axis can be interpreted as a line whose slope can be directly computed from v_1. Additionally,λ_1 and λ_2 can be used to compute the eccentricity $\sqrt{1-\sqrt{\lambda_2}/\sqrt{\lambda_1}}$ as a metric for the shape of the distribution. Both constraints are associated with this eigen analysis. The first constraint is that the slope must exceed a minimum of 0.003. The second constraint is that the eccentricity has to exceed a minimum of 0.2.

B. Face Extraction

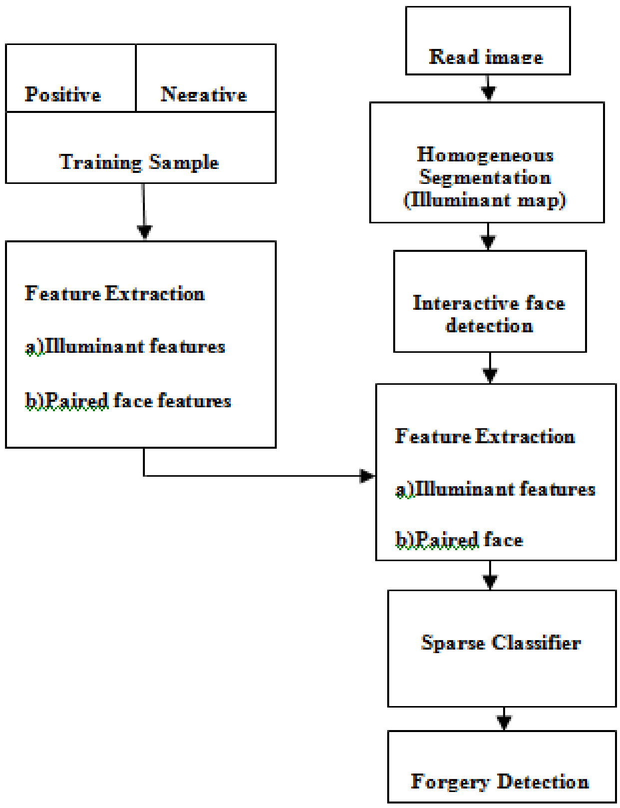

Fig: 3. Architecture of the proposed work

Face extraction reruire bounding boxes around all faces in an image that should be part of the investigation. For obtaining the bounding boxes, we could in principle use an automated algorithm, e.g., the one by Schwartz *et al.* [15]. However, we prefer a human operator for this task for two main reasons: a) this minimizes false detections or missed faces; b) scene context is important when judging the lighting situation. For instance, consider an image where all persons of interest are illuminated by flashlight. The illuminants are expected to agree with one another. Conversely, assume that a person in the foreground is illuminated by flashlight, and a person in the background is illuminated by ambient light. Then, a difference in the color of the illuminants is expected. Such differences are hard to distinguish in a fully-automated manner, but can be easily excluded in manual annotation.

C. Texture Description: SASI Algorithm

Here use the Statistical Analysis of Structural Information (SASI) descriptor by Carkacioglu and Yarman-Vural [16] to extract texture information from illuminant maps. Recently, Penatti *et al.* [17] pointed out that SASI performs remarkably well. For our application, the most important advantage of SASI is its capability of capturing small granularities and discontinuities in texture patterns. 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. 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. One autocorrelation is computed using a specific fixed orientation, scale, and shift. Computing the mean and standard deviation of all such pixel values yields two feature dimensions. Repeating this computation for varying orientations, scales and shifts yields a 128-dimensional feature vector. As a final step, this vector is normalized by subtracting its mean value, and dividing it by its standard deviation.

D. Interpretation of Illuminant Edges: HOG edge Algorithm

Differing illuminant estimates in neighboring segments can lead to discontinuities in the illuminant map. Dissimilar illuminant estimates can occur for a number of reasons: changing geometry,

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

changing material, noise, retouching or changes in the incident light. Thus, one can interpret an illuminant estimate as a low-level descriptor of the underlying image statistics. It is observed that the edges, e.g., computed by a canny edge detector, detect in several cases a combination of the segment borders and isophotes (i.e., areas of similar incident light in the image). When an image is spliced, the statistics of these edges is likely to differ from original images. To characterize such edge discontinuities, here propose a new feature descriptor called *HOGedge*. It is based on the well-known HOG-descriptor, and computes visual dictionaries of gradient intensities in edge points. Fig. 4 shows an algorithmic overview of the method. In this first extract approximately equally distributed candidate points on the edges of illuminant maps. At these points, HOG descriptors are computed. These descriptors are summarized in a visual words dictionary. Each of these steps is presented in greater detail in the next subsections.

Extraction of Edge Points: Given a face region from an illuminant map, first extract edge points using the canny edge detector [17]. This yields a large number of spatially close edge points. To reduce the number of points, filter the canny output using the following rule: starting from a seed point, we eliminate all other edge pixels in a region of interest (ROI) centered on the seed point. The edge points that are closest to the ROI (but outside of it) are chosen as seed points for the next iteration. By iterating this process over the entire image, reduce the number of points but still ensure that every face has a comparable density of points. HOG is based on normalized local histograms of image gradient orientations in a dense grid. The HOG descriptor is constructed around each of the edge points. The neighborhood of such an edge point is called a cell. Each cell provides a local 1-D histogram of quantized gradient directions using all cell pixels. To construct the feature vector, the histograms of all cells within a spatially larger region are combined and contrast- normalized. After edge extraction, go for selection of faces in the image. The next step is totally a manual process.

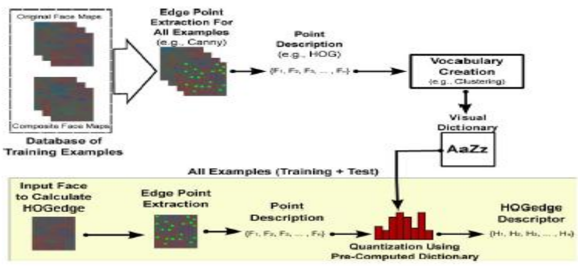

Fig: 4 Overview of the HOG edge algorithm

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

E. Face Pair

To compare two faces, first combine the same descriptors for each of the two faces.For instance, can concatenate the SASI-descriptors that were computed on gray world. The idea is that a feature concatenation from two faces is different when one of the faces is an original and one is spliced. For an image containing n_f faces, ($n_f \geq 2$), the number of face pairs is $(n_f\,(n_f - 1))/2$.

The SASI and HOGedge descriptors capture two different properties of the face regions. From a signal processing point of view, both descriptors are *signatures* with different behavior. This experiment empirically demonstrates two points. Firstly, SASI and HOGedge, in combination with the IIC-based and gray world illuminant maps create features that discriminate well between original and tampered images, in at least some dimensions. Secondly, the dimensions, where these features have distinct value, vary between the four combinations of the feature vectors. Thus exploit this property during classification by fusing the output of the classification on both feature sets.

F. Classification

In this section classify the illumination for each pair of faces in an image as either consistent or inconsistent. Assuming all selected faces are illuminated by the same light source, then tag an image as manipulated if one pair is classified as inconsistent. Individual feature vectors, i.e., SASI or HOG edge features on either gray world or IIC-based illuminant maps, are classified using a sparse classifier with a radial basis function (RBF) kernel. The information provided by the SASI features is complementary to the information from the HOG edge features. Thus, use a machine learning-based fusion technique for improving the detection performance. Inspired by the work of Ludwig *et al.* [19], Here classify each combination of illuminant map and feature type independently (i.e., SASI-Gray-World, SASI-IIC, HOG edge-Gray-World and HOG edge-IIC) using a sparse classifier to obtain the distance between the image's feature vectors and the classifier decision boundary. The sparse classifier is having high detection rate and requires minimum amount of human interaction.

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 4) Pages (122-135)

Journal home page: www.ijreb.org

CONCLUSION AND FUTURE WORK

A new method for detecting forged images of people using the illuminant color is used in the system. This method estimates the illuminant color using a statistical gray edge method and a physics-based method which exploits the inverse intensity- chromaticity color space. Thus the proposed method requires only a minimum amount of human interaction and provides a crisp statement on the authenticity of the image. Additionally, it is a significant advancement in the exploitation of illuminant color as a forensic cue. The sparse classifier faster and it has high performance in the classification process. As future work, further more improvements can be achieved by using more advanced illuminant color estimators. Reasonably effective skin detection methods have been presented in the computer vision literature in the past years. Incorporating such techniques can further expand the applicability of this method. Such an improvement could be used in detecting pornography compositions.

REFERENCES

[1]. C. Riess and E. Angelopoulou, "Scene illumination as an indicator of image manipulation," vol. 6387, pp. 66–80,(2011).

[2]. M. Johnson and H. Farid, "Exposing digital forgeries through specular highlights on the eye," Workshop on Inform.Hiding, (2007), pp. 311–325.

[3]. E. Kee and H. Farid,"Exposing digital forgeries from 3-D lighting environments," workshop on inform.forencics and security(WIFS), Dec. (2010), pp. 1–6.

[4]. X.Wu and Z. Fang, "Image splicing detection using illuminant color inconsistency," Multimedia Inform. Networking and Security, Nov.(2011), pp. 600–603.

[5]. P. Saboia, T. Carvalho, and A. Rocha, "Eye specular highlights telltales for digital forensics: A machine learning approach," Image Processing (ICIP),(2011)

[6]. A. Gijsenij,R.Lu, and T. Gevers, "Color constancy for multiple light sources," vol. 21, no. 2, pp. 697–707, Feb.(2012).

[7]. S. Bianco and R. Schettini,"Color constancy using faces," Vision and Pattern Recognition, Providence, RI, USA,Jun.(2012).

[8]. J. van de Weijer, T. Gevers, and A. Gijsenij, "Edge-based color constancy," vol. 16, no. 9, pp. 2207–2214,Sep. (2007).

IJREB
ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 4) Pages (122-135)
Journal home page: www.ijreb.org

[9] E. Kee and H. Farid, "Exposing digital forgeries from 3-D lighting environments,"in *Proc. IEEE Int. Workshop on Inform. Forensics and Security (WIFS)*, Dec. 2010, pp. 1–6.

[10] W. Fan, K. Wang, F. Cayre, and Z. Xiong, "3D lighting-based image forgery detection using shape-from-shading," in *Proc. Eur. Signal Processing Conf. (EUSIPCO)*, Aug. 2012, pp. 1777–1781.

[11] J. F. O'Brien and H. Farid, "Exposing photo manipulation with inconsistent reflections," *ACM Trans. Graphics*, vol. 31, no. 1, pp. 1–11, Jan. 2012.

[12] S. Gholap and P. K. Bora, "Illuminant colour based image forensics," in *Proc. IEEE Region 10 Conf.*, 2008, pp. 1–5.

[13] X.Wu and Z. Fang, "Image splicing detection using illuminant color inconsistency," in *Proc. IEEE Int. Conf. Multimedia Inform. Networking and Security*, Nov. 2011, pp. 600–603.

[14] P. F. Felzenszwalb and D. P. Huttenlocher, "Efficient graph-based image segmentation," *Int. J. Comput. Vis.*, vol. 59, no. 2, pp. 167–181, 2004.

[15] G. Buchsbaum, "A spatial processor model for color perception," *J. Franklin Inst.*, vol. 310, no. 1, pp. 1–26, Jul. 1980.

[16] A. Carkacioglu and F. T. Yarman-Vural, "Sasi: A generic texture descriptor for image retrieval," *Pattern Recognit.*, vol. 36, no. 11, pp. 2615–2633, 2003

[17] O. A. B. Penatti, E. Valle, and R. S. Torres, "Comparative study of global color and texture descriptors for web image retrieval," *J. Visual Commun. Image Representat.*, vol. 23, no. 2, pp. 359–380, 2012.

[18] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Secaucus, NJ, USA: Springer-Verlag New York, Inc, 2006.

[19] O. Ludwig, D. Delgado, V. Goncalves, and U. Nunes, "Trainable classifier- fusion schemes: An application to pedestrian detection," in *Proc. IEEE Int. Conf. Intell. Transportation Syst.*, 2009, pp. 1–6.