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Digital Image Forgery Detection by Illumination Color Classification

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Abstract— Nowadays It is very easy to manipulate and edit the digital images because of availability of powerful image processing tools and editing software. Everyday millions of digital documents are produced by variety of devices 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. Generally Photographs are served as evidence in courts. The most common forms of photographic manipulation, i.e. image splicing or also known as image composition is analyzed in this paper. It is difficult to adjust the illumination condition when Image composition or splicing operation performed on image to create composite image In this project we propose a forgery detection method that find out the inconsistencies in the color of the illumination of images. Our approach in this project is based on machine learning and requires very limited user interaction. This technique is applicable to images with two or more people and requires no expert interaction for making the decision. To achieve this, we apply physics and statistical based illuminant estimators on image areas of similar material. From these illuminant estimators, we extract texture and edge based features of the images which are then provided to a machine learning approach i.e. to a classifier for automatic decision making.
For that here we use the SVM classifier for the forensic detection. Automatic face detection is used in order to improve the accuracy of the result.

Keywords— lluminant Map, Classifier, Forgery, Illuminant Estimators.

I. INTRODUCTION

In today's age it is very easy to manipulate the images. Many advanced digital images editing software's are available. Millions of digital documents are created and distributed by Magazine, newspapers and TV. 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.

Image composition (or splicing) is one of the most common image manipulation operations. One such example is shown in Fig. 1. 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 viewpoint of a manipulator, proper adjustment of the illumination conditions is hard to achieve when creating a composite image [2]

In this spirit, Rises and Angelopoulos [3] proposed to analyze illuminant color estimates from local image regions. Unfortunately, the interpretation of their resulting so-called *illuminant maps* is left to human experts. As it turns out, this decision is, in practice, often challenging. Moreover, relying on visual assessment can be misleading, as the human visual system is quite inept at judging illumination environments in pictures [4], [5]. Thus, it is preferable to transfer the tampering decision to an objective algorithm.

In this work, we make an important step towards minimizing user interaction for an illuminant based tampering decision making. We propose the method to detect the forensic in the photography. We combine the HOG and SASI features and we use the SVM classifier for the forensic detection.

Fig 1:- Forensic Image

II. RELATED WORKS

Illumination-based approaches for forgery detection are either color based or geometry based. Geometry based approaches focus at identifying inconsistencies in light source positions between specific objects in the scene.[6]-[12] Color-based approaches examine for inconsistencies in the interactions between object color and light color. [3]Two approaches have been suggested that usage the direction of the incident light for exposing digital forgeries. [8]Johnson and Farid suggested a method which calculates a low-dimensional descriptor of the lighting environment in the image plane (i.e., in 2-D). It calculates the illumination direction from the intensity distribution along physically annotated object boundaries of similar color. Kee and Farid [9] extended this method to manipulating known 3-D surface geometry. In the instance of faces, a dense grid of 3-D normals improves the estimate of the illumination direction. To do this, a 3-D face model is registered with the 2-D image using physically annotated facial landmarks.[8] Johnson and Farid also suggested composite image detection by exploiting specular highlights in the eyes. In a subsequent extension, Saboia et al. automatically classified composite images by extracting extra features, such as the viewer position. The applicability of both methods, however, is somewhat restricted by the fact that people's eyes must be visible and available in high resolution. Gholap and Bora presented physics-based illumination cues to image forensics. The authors observed variations in specularities based on the dichromatic reflective model. Specularity segmentation on realistic images is challenging.

Therefore, the authors require physical annotation of specular highlights. Additionally, specularities have to be present on all areas of interest, which bounds the method's applicability in real-world scenarios. To avoid this problem, Wu and Fang adopt purely diffuse (i.e., specular-free) reflectance, and train a mixture of Gaussians to choose a appropriate illuminant color estimator. The angular distance to illuminant estimates from selected regions can then be used as an indicator for tampering. Unfortunately, the technique requires the physical selection of a "reference block", where the color of the illuminant can be consistently estimated. This is a important restriction of the technique. Riess and Angelopoulou followed a different method by using a physics-based color constancy algorithm that works on partially specular pixels. In this method, the automatic finding of highly specular regions is avoided. The authors suggest slicing the image to estimate the illuminant color locally per segment. Recoloring every image region giving to its local illuminant estimate yields a so-called illuminant map. Improbable illuminant color estimates point towards a worked region. Unfortunately, the authors do not offer a numerical decision criterion for tampering detection. In the field of color constancy, descriptors for the illuminant color have been widely studied. Most research in color constancy focuses on consistently illuminated scenes containing a single dominant illuminant. Though, in order to use the color of the incident illumination as a sign of image tampering, we require various, spatially-bound illuminant estimates. So far, limited work has been done in this dire Ebner discussed an early approach to multi-illuminant estimation. Assuming smoothly blending illuminants, the author proposes a diffusion process to recover the illumination distribution. Unfortunately, in practice, this approach over smooth's the illuminant borders. Gijsenij et al. offered a pixel wise illuminant estimator. It permits segmenting an image into regions illuminated by different illuminants. Differently illuminated regions can have crisp changes, for example between sunlit and shadow areas. Although this is an interesting approach, a single illuminant estimator can constantly fail. Hence, for forensic purposes, we select a scheme that combines the results of various illuminant estimators.

Previously, Kawakami et al. suggested a physics-based method that is custom-tailored for discriminating shadow/sunlit areas.In this work, we build upon the ideas by and. We use the comparatively rich illumination information provided by both statistics based color and physics-based constancy approaches. Decisions with respect to the illuminant color estimators are totally taken away from the user, which distinguishes this work from previous work.

III. PROPOSED WORK

In this project we propose the method to detect the forensic in the photography. For that here we use the SVM classifier for the forensic detection. Initially we identify the illuminant map in the image. We find the face from the photography. For the face detect here we use the violo john method. After face detection we crop the face image and calculate the canny edge and HOG feature. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms.

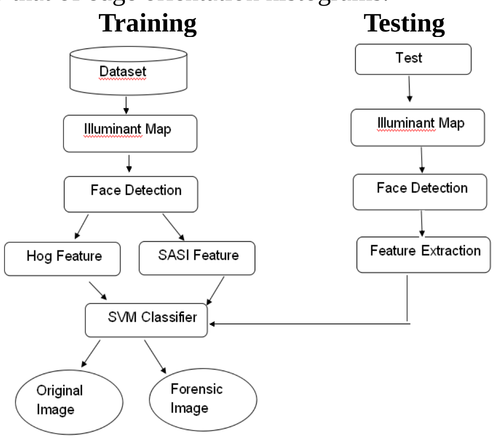

Fig 2 :- System Architecture

The method extracts invariance to geometric and photometric transformations for object orientation. Then we calculate the Local Binary Patterns of the image. After that we identify the Statistical analysis of structure Information (SASI). In SASI the statistical information of the image such as energy, entropy, correlation sum of energy and sum of correlation are calculated. The extracted feature will pass to the SVM classifier for the training. SVM is stands for Support vector machine. It is a binary classifier. It is a kernel based learning classifier. The trained classifier will predict about the image whether it is original or forensic image.

Hog Feature Descriptor:

Histogram of oriented gradients (HOG) is a feature descriptor used to detect objects in computer vision and image processing. The HOG descriptor technique counts occurrences of gradient orientation in localized portions of an image - detection window, or region of interest (ROI).

Implementation of the HOG descriptor algorithm is as follows:

- Divide the image into small connected regions called cells, and for each cell compute a histogram of gradient directions or edge orientations for the pixels within the cell.
- Discretize each cell into angular bins according to the gradient orientation.
- Each cell's pixel contributes weighted gradient to its corresponding angular bin.
- Groups of adjacent cells are considered as spatial regions called blocks. The grouping of cells into a block is the basis for grouping and normalization of histograms.
- Normalized group of histograms represents the block histogram. The set of these block histograms represents the descripto

The proposed method consists of five main components:

A. Illuminant Estimation (IE):

The input image is segmented into homogeneous regions. Per illuminant estimator, a new image is created where each region is colored with the extracted illuminant color. This resulting intermediate representation is called illuminant map (IM).

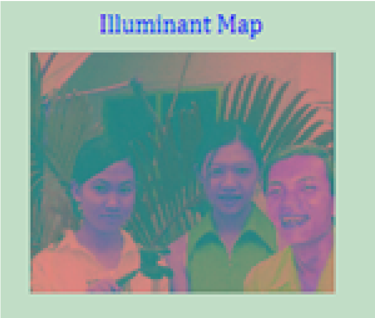

Fig 3 :- Illuminant Map

B. Face Extraction:

An automated face detector is employed.

C. Illuminant Features Computation:

For all face regions, texture-based and gradient based features are computed the IM values. Each one of them encodes complementary information for classification.

1) SASI (Statistical Analysis of Structural Information):-

We use the Statistical Analysis of Structural Information (SASI) descriptor by Carkacioglu and Yarman-Vural [31] to extract texture information from illuminant maps. Recently, Penatti et al. [32] 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 auto correlation of horizontal, vertical and diagonal pixel lines over an image at different scales. Instead of computing the auto correlation 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.

2) Hogedge Algorithm (HOG):

Differing illuminant estimates in neighbouring segments can lead to discontinuities in the illuminant map. Dissimilar illuminant estimates can occur for a number of reasons changing geometry, 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. We 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, we 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. We first extract approximately equally distributed candidate points on the edges of illuminant maps. At these points, HOG descriptors are computed.

D. Features of Paired Face:

Our goal is to assess whether a pair of faces in an image is consistently illuminated. For an image with faces, we construct joint feature vectors, consisting of all possible pairs of faces.

E. Classification:

We use a machine learning approach to automatically classify the feature vectors. We consider an image as a forgery if at least one pair of faces in the image is classified as inconsistently illuminated.

V. EXPECTED RESULTS

The regular images have been taken for the analysis of the project. The probable results are obtained from both the original and spliced images.

V. CONCLUSIONS

In this approach, new technique for detecting forged images of people using the illuminant color has been discussed. The illuminant colors a physics-based method and using a statistical gray edge method which exploits the inverse intensity chromaticity color space has been estimated. This illuminant map is treated as texture maps. An information on the distribution of edges on illuminant maps are extracted.

In order to define the edge information, a new algorithm based on the HOG descriptor and edge-points, called HOGedge is proposed. Respectable results are also achieved over internet images and under cross-database training/testing. The proposed method requires only a least amount of human interaction and provides a crisp statement on the authenticity of the image. Additionally, it is a major progress in the exploitation of illuminant color as a forensic cue .

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