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SVM Classifier-Based Automatic Machine Learning Forgery Identification

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ABSTRACT

Composites of analog images may be produced by photographers; however, this technique takes a lot of time and requires specialized skills. Modifications to digital images are made easily using the editing program. This project examines picture composition, often known as splicing, which is one of the most popular types of photography alteration. For that purpose, a fraud detection technique is used to take advantage of minute variations in the color of an image's lighting. Images with two or more persons may be used with the machine learning approach. This idea is accomplished by using data from statistical (texture and edge) and physics (chromaticity)-based illumination estimators on picture portions of related images. A machine-learning technique is then given the extracted texture, skin pigmentation, and edge-based data for automated decision-making. An SVM (Support Vector Machine) meta-fusion classifier's classification performance.

Index Terms: texture and edge descriptors, spliced image detection, machine learning, color constancy, illuminant color, and picture forensics.

I.INTRODUCTION

One of the most popular methods of picture alteration is image composition. The 2011 Benetton Un-Hate advertising campaign1 or the diplomatically delicate case in which an Egyptian state-run newspaper published a manipulated photograph of Egypt's former president, Hosni Mubarak, at the front rather than the back of a group of leaders meeting for Using every source of tampering evidence at their disposal, forensic investigators evaluate an image's legitimacy. lighting inconsistencies are among the other indicators that may be useful for splicing detection: from the perspective of a manipulator, it is difficult to properly change the lighting circumstances while constructing a composite picture [1].

In keeping with this idea, Riess and Angelopoulou [2] suggested using local picture areas to examine illuminant color estimations. Unfortunately, it is up to human specialists to analyze the so-called illuminant maps they produce. It turns out that in reality, this choice is often difficult.

We take a significant stride in our study to reduce user engagement for altering decision-making based on illumination. We suggest a novel semiautomatic technique that is also much more dependable than previous methods. We take use of the fact that when comparing objects of the same (or comparable) material, local illuminant estimations are the most discriminative.

Therefore, the project's primary goal is to automatically compare human skin—more especially, faces—in order to determine if two faces' lighting is consistent or inconsistent. The only way the user may interact with a picture under inspection is by drawing bounding boxes around the faces. In the most basic scenario, this just means defining a bounding box's top left and lower right corners. In conclusion, this work's primary contributions are:

- Using the light distribution as an object texture to calculate features.
- A new edge-based characterisation technique that investigates edge characteristics associated with the illumination process for illuminant maps.
- The development of a reference dataset consisting of 100 well crafted fakes and 100 authentic images3.

II. LITERATURE SURVEY

llumination-based methods for forgery detection are either geometry-based or color-based. Geometry-based methods focus at detecting inconsistencies in light source positions between specific objects in the scene [5]–[11]. Color-based methods search for inconsistencies in the interactions between object color and light color [2], [12], [13].

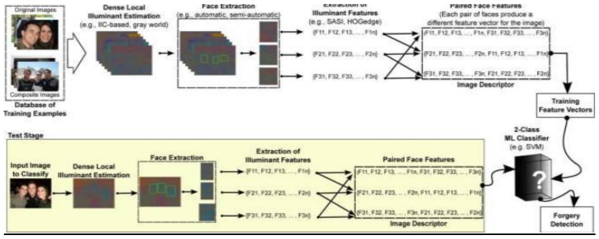
Johnson and Farid [8] also proposed spliced image detection by exploiting specular highlights in the eyes. In a subsequent extension, Saboia *et al.* [14] automatically classified these imagesby extracting additional features, such as the viewer position. The applicability of both approaches, however, is somewhat limited by the fact that people’s eyes must be visible and available in high resolution.

Gholap and Bora [12] introduced physics-based illumination cues to image forensics. The authors examined inconsistencies in specularities based on the dichromatic reflectance model. Specularity segmentation on real-world images is challenging [15]. Therefore, the authors require manual annotation of specular highlights. Additionally, specularities have to be present on all regions of interest, which limits the method’s applicability in real-world scenarios. To avoid this problem, Wu and Fang [13] assume purely diffuse (i.e., specular-free) reflectance, and train a mixture of Gaussians to select a proper illuminant color estimator.

Challenges In Exploiting Illuminant Maps

We quickly review the illuminant maps produced by the Riess and Angelopoulou approach [2] to highlight the difficulties of directly using illuminant estimations. This method divides a picture into superpixels, or areas of comparable color. The pixels within each superpixel are used to locally estimate an illuminant color (see [2] and Section IV-A for details). An illuminant map is created by recoloring each superpixel using its estimated local illuminant hue. The input picture and the illuminant map may then be examined by a human specialist to look for discrepancies. Therefore, even if illuminant maps provide a crucial intermediate representation, we stress that automated processing is necessary to prevent skewed or questionable human judgments. As a result, we suggest a pattern recognition system that uses illuminant maps.

Together with the color distribution, the characteristics are made to capture the super pixels' form. In keeping with this, our objective is to eliminate the need for the expert-in-the-loop by only needing facial annotations in the picture.



III. Automatic Machine Learning Forgery Detection

We classify the illumination for each pair of faces in the image as either consistent or inconsistent. Throughout the paper, we abbreviate illuminant estimation as IE, and illuminant maps as IM. The proposed method consists of five main components:

1. **Dense Local 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).

2. *Face Extraction:*

This is the only step that may require human interaction. An operator sets a bounding box around each face in the image that should be investigated. Alternatively, an automated face detector can be employed. then crop every bounding box out of each illuminant map.

3. *Computation of Illuminant Features:*

For all face regions, texture-based and gradient- based features are computed the IM values. Each one of them encodes complementary information for classification. *4.Paired Face Features:*

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.

5. *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.

Figure1 shows the Overview of the proposed method.

1 .Illuminant Estimation (IE):

Felzenszwalb and Huttenlocher's technique [25] divides the input picture into superpixels, or areas of roughly constant chromaticity, in order to calculate a dense collection of localized illuminant color estimations. The illuminant's color is approximated per superpixel.
primarily makes use of two distinct illuminant color estimators: the physics-based inverse-intensity chromaticity space and the statistical generalized gray world estimations.
Assume that $f(x)=(fR(x),fG(x),fB(x))T$ represents the observed

A pixel's RGB color at a certain position. The assumptions used by Van deWeijer et al. [23] are linear camera response and completely diffuse reflection.
$e(\lambda,X)s(\lambda,x)c(\lambda)d\lambda = \int\Omega\ F(x)$

- •Derivative order: The absolute value of the sum of the image's derivatives may be related to the achromatic average of the illuminants.
- •Minkowski norm: By calculating the Minkowski norm of these quantities, more robustness may be attained rather than just adding intensities or derivatives, respectively.
- • Gaussian smoothing: Before processing a picture, it may be smoothed using a Gaussian to decrease noise.

2 Face Extraction

Every face in a picture that should be included in the inquiry must have bounding boxes around it. In theory, we could utilize an automated technique to obtain the bounding boxes. However, there are two primary reasons why we favor a human operator for this task: This reduces missing faces or incorrect detections; b) scene context is crucial for assessing the lighting conditions.
For example, imagine a picture in which a torch illuminates every individual of interest. It is predicted that the illuminants will concur with each other. Assume, on the other hand, that ambient light illuminates a person in the background and a flashlight illuminates a person in the front. It is thus

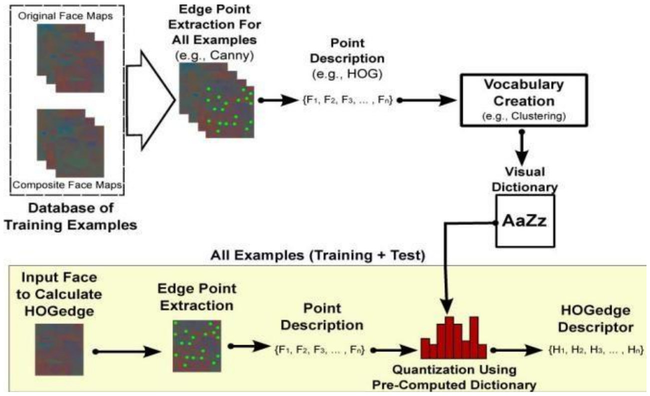
anticipated that the illuminants' colors would vary. In a completely automated system, these distinctions are difficult to discern.

2.Illuminant Features

Texture Description: SASI Algorithm

We use the Statistical Analysis of Structural Information (SASI) descriptor by Carkacioglu and Yarman- Vural [13] to extract texture information from illuminant maps. 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.



underlying image statistics.We observed that the edges, e.g., computed by a Canny edge detector,

Extraction of Edge Points:

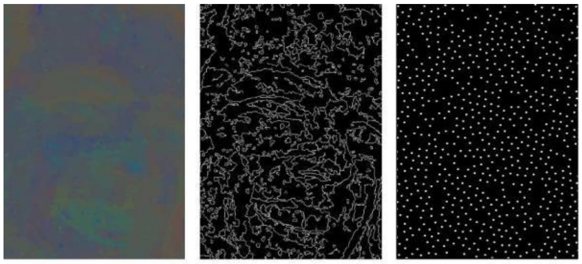
Given a face region from an illuminant map, we first extract edge points using the Canny edge detector [33]. This yields a large number of spatially close edge points. To reduce the number of points. Figure2 and figure3 Shows the Overview of the proposed H OGedge algorithm

Point Description:

We compute Histograms of Oriented Gradients (HOG) [34] to describe the distribution of the selected edge 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.

Visual Vocabulary:

The number of extracted HOG vectors varies depending on the size and structure of the face under examination. We use visual dictionaries [35] to obtain feature vectors of fixed length. Visual dictionaries constitute a robust representation, where each face is treated as a set of region descriptors. The spatial location of each region is discarded [16].



(a) (b) (c)

Figure 3: (a) Gray world IM for the left face in Fig. 6(a). (b) Result of the Canny edge detector when applied on this IM. (c) Final edge points after filtering using a square region. (a) IM derived from gray world. (b) Canny Edges.
(c) Filtered Points.

Interpretation of Illuminant Edges: Hogedge 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, changing material, noise, retouching or changes in the incident light. Thus, one can interpret an illuminant estimate as a low-level descriptor of the To construct our visual dictionary, we subdivide the training data into feature vectors from original and doctored images. Each group is clustered in clusters using the -means algorithm [15]

```
Algorithm
HOGedge—Visual dictionary creation
Require: $V_{TR}$(training database examples) (the number of visual words per class)
Ensure: $v_{D}$(visual dictionary containing visual words)
$v_{D} \leftarrow Ø$;
$v_{NF} \leftarrow Ǿ$;
$v_{DF} \leftarrow Ø$;
for each face IM do
  $V_{EP} \leftarrow$ edge points extracted from i ;
  for each point j£ $V_{EP}$ do
    FV $\leftarrow$ apply HOG in image at position ;
If i is a doctored face then
        $v_{DF} \leftarrow \{ v_{DF}$ Ụ FV};
else
        $V_{NF} \leftarrow \{ V_{NF}$ Ụ FV};
        end if
end for
end for
Cluster $v_{DF}$ usin n centers;
Cluster $v_{NF}$ using n centers;
return ;
```

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. Fig. 9 shows a very high-level visualization of the distinct information that is captured by these two descriptors. For one of the folds of our experiments (see Section V-C), we computed the mean value and standard deviation per feature dimension. For a less cluttered plot, we only visualize the feature dimensions with the largest difference in the mean values for this fold. This experiment empirically demonstrates two points. Firstly, SASI and HOG edge, 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.

6. Classification

We 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, tag an image as manipulated if one pair is classified as inconsistent. Individual feature vectors SASI or HOGedge features on either gray world or IIC-based illuminant maps, are classified using a support vector machine (SVM) classifier with a radial basis function (RBF).

The information provided by the SASI features is complementary to the information from the HOGedge features. Thus, we use a machine learning-based fusion technique for improving the detection performance.

IV. EXPERIMENTS AND RESULTS

Evaluation Data

To quantitatively evaluate the proposed algorithm, and to compare it to related work, we considered two datasets. One consists of images that we captured ourselves, while the second one contains images collected from the internet. Additionally, validated the quality of the forgeries using a human study on the first dataset. Human performance can be seen as a baseline for our experiments.

1. *DSO-1:*This is our first dataset and it was created by ourselves. It is composed of 200 indoor and outdoor images with an image resolution of . Out ofthis set of images, 100 are original, have no adjustments whatsoever, and 100 are forged. The forgeries were created by adding one or more individuals in a source image that already contained one or more persons. 2. *DSI-1:*This is our second dataset and it is composed of 50images (25 original and 25 doctored downloaded fromdifferent websites in the Internet with different resolutions5. Figure. 4 depicts the average gray image of a input image ie. the gray estimation .

Figure 4. Gray estimation

Figure 5.Image deviation

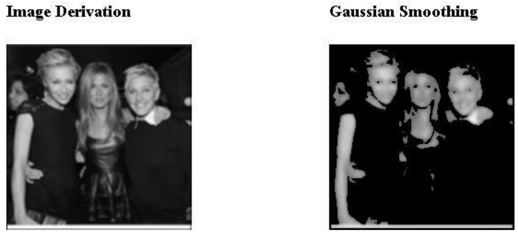


Figure 6. gaussian smoothing

Figure 7. face extraction

V. CONCLUSION FUTURE WORK

In this study, we introduced a novel technique that uses the illuminant color to identify phony human photos. A statistical gray edge technique and a physics-based approach that takes use of the inverse intensity-chromaticity color space are used to determine the illuminant color. These illuminant maps are handled as texture maps. Additionally, we extract data on the distribution of edges on these maps. We provide a novel approach based on edge-points and the HOG to characterize the edge information. Figure 15. HOGedge is a cross-database experiment descriptor that provides the ROC curve. We integrate these complimentary signals (edge- and texture-based

Using late fusion in machine learning.
It also represents a major breakthrough in the use of illuminant hue as a forensic cue. Previous color-based work imposes highly restrictive assumptions or requires complicated user engagement. In subsequent projects In recent years, computer vision literature has proposed skin detection techniques that are quite successful. Our method's usefulness may be further expanded by using similar strategies. Such an advancement may be used, for example, to identify pornographic compositions, which forensic experts say are becoming more and more prevalent these days.

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