Automatic Machine Learning Forgery Detection Based on SVM Classifier

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ABSTRACT
Photographers are able to create composites of analog pictures, this process is very time consuming and require expert knowledge. In digital image the editing software makes modifications in straight forward. In this project analyze one of the most common form of photographic manipulation known as image composition or splicing. For that propose a forgery detection method is used to exploits subtle inconsistencies in the colour of the illumination of images. The technique (**Machine Learning**) is applicable to images containing two or more people. To achieving this concept, the information from physics (**chromaticity**)-and statistical (**texture and edge**)-based illuminate estimators on image regions of similar images are taken. Then the extracted texture, skin pigmentation- and edge-based features are provided to a machine-learning approach for automatic decision-making. The **classification** performance achieved by an **SVM (Support Vector Machine)** meta-fusion classifier.

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

I.INTRODUCTION

Image composition is one of the most common form of image manipulation operations. Although in an image a harmless manipulation case, several more controversial cases have been reported, e.g., 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 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 [1].

In this spirit, Riess and Angelopoulou [2] 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.

In this work, we make an important step towards minimizing user interaction for an illuminant-based tampering decision- making. We propose a new semiautomatic method that is also significantly more reliable than earlier approaches. We exploit the fact that local illuminant estimates are most discriminative when comparing objects of the same (or similar) material.

Thus, the project mainly focus on the automated comparison of human skin, and more specifically faces, to classify the illumination on a pair of faces as either consistent or inconsistent. User interaction is limited to marking bounding boxes around the faces in an image under investigation. In the simplest case, this reduces to specifying two corners (upper left and lower right) of a bounding box. In summary, the main contributions of this work are:

•Interpretation of the illumination distribution as object texture for feature computation.
• A novel edge-based characterization method for illuminant maps which explores edge attributes related to the illumination process.
• The creation of a benchmark dataset comprised of 100 skillfully created forgeries and 100 original photographs3.

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

To illustrate the challenges of directly exploiting illuminant estimates, we briefly examine the illuminant maps generated by the method of Riess and Angelopoulou [2]. In this approach, an image is subdivided into regions of similar color (superpixels). An illuminant color is locally estimated using the pixels within each superpixel (for details, see [2] and Section IV-A). Recoloring each superpixel with its local illuminant color estimate yields a so-called *illuminant map*. A human expert can then investigate the input image and the illuminant map to detect inconsistencies. Thus, while illuminant maps are an important intermediate representation, we emphasize that further, automated processing is required to avoid biased or debatable human decisions. Hence, we propose a pattern recognitionscheme operating on illuminant maps.

The features are designed to capture the shape of the super pixels in conjunction with the color distribution. In this spirit, our goal is to replace the expert-in-the-loop, by only requiring annotations of faces in the image.

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.

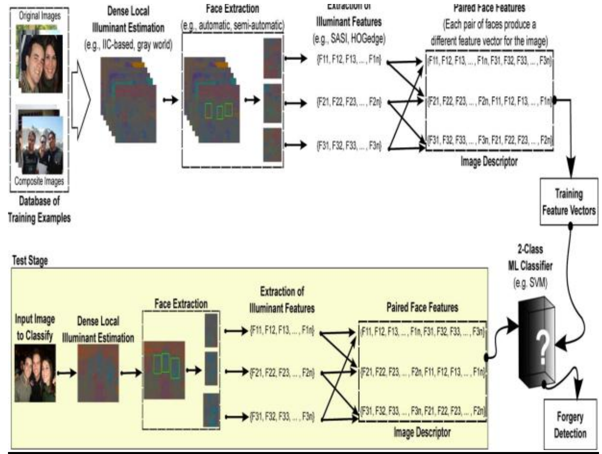


Figure 1: Overview of the proposed method

1 .Illuminant Estimation (IE):

To compute a dense set of localized illuminant color estimates, the input image is segmented into superpixels, i.e., regions of approximately constant chromaticity, using the algorithm by Felzenszwalb and Huttenlocher [25]. Per superpixel, the color of the illuminant is estimated.
Mainly here uses two separate illuminant color estimators: the statistical generalized gray world estimates and the physics-based inverse-intensity chromaticity space,
Let $f(x)=(f_R(x),f_G(x),f_B(x))^T$ denote the observed RGB color of a pixel at location . Van deWeijer *et al.* s[23] assume purely diffuse reflection and linear camera response.

$$\mathbf{F(x)=\int_{\Omega} e(\lambda,X)s(\lambda,x)c(\lambda)d\lambda}$$

• Derivative order :

The assumption that the average of the illuminants is achromatic can be extended to the absolute value of the sum of the derivatives of the image.

• Minkowski norm :

Instead of simply adding intensities or derivatives, respectively, greater robustness can be achieved by computing the Minkowski norm of these values.

• Gaussian smoothing :

To reduce image noise, one can smooth the image prior to processing with a Gaussian.

2. Face Extraction

We require 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. 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

3. 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.

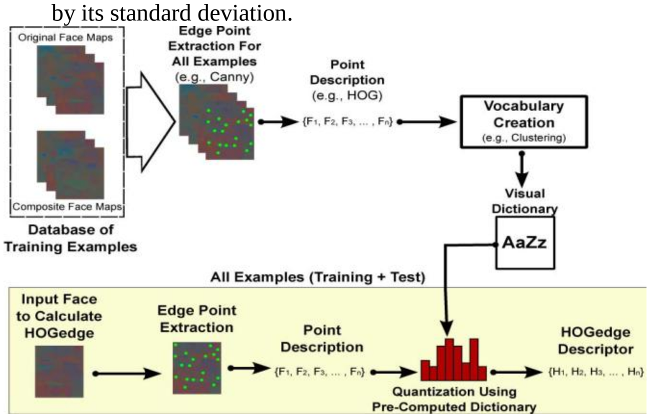
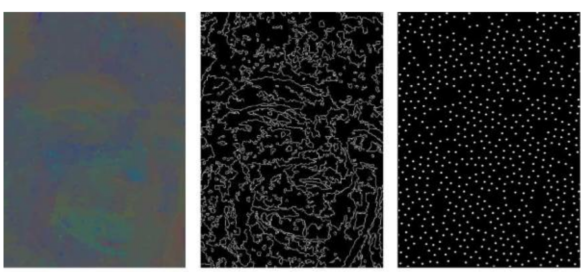


Figure2.Overview of the proposed H OGedge algorithm



(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 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].

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**
    $v_{DF} \leftarrow \{ v_{DF} \cup FV\}$;
else
    $V_{NF} \leftarrow \{ V_{NF} \cup FV\}$;
    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.

5. 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 .

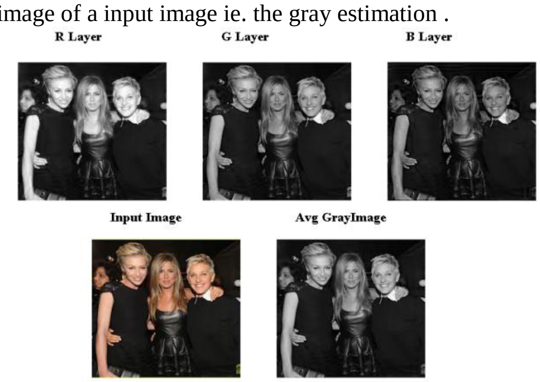


Figure 4. Gray estimation

Figure 5.Image deviation

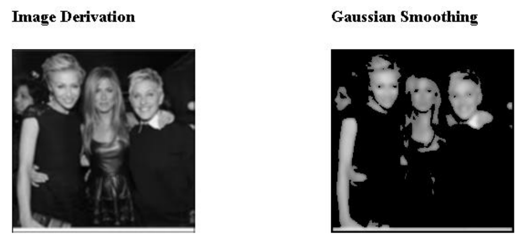


Figure 6. gaussian smoothing

Figure 7. face extraction

V.CONCLUSION FUTURE WORK

In this work, we presented a new method for detecting forged images of people using the illuminant color. We estimate the illuminant color using a statistical gray edge method and a physics-based method which exploits the inverse intensity-chromaticity color space. We treat these illuminant maps as
texture maps. We also extract information on the distribution of
edges on these maps.In order to describe the edge information, we propose a new algorithm based on edge-points and the HOG Fig. 15. ROC curve provided by cross-database experiment. descriptor, called HOGedge. We combine these complementary cues (texture- and edge-baed) using machine learning late fusion.

Additionally, it is a significant advancement in the exploitation of illuminant color as a forensic cue. Prior color-based work either assumes complex user interaction or imposes very limiting assumptions. In future work Reasonably effective skin detection methods have been presented in the computer visi on literature in the past years. Incorporating such techniques can further expand the applicability of our method. Such an improvement could be employed, for instance, in detecting pornography compositions which, according to forensic practitioners, have become increasingly common nowadays.

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