# Detection of Digital Image Splicing Using Luminance

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**Abstract**
The availability of photo manipulation software has made it unprecedentedly easy to manipulate images for malicious purposes .The analyzation of images and detection of one of the most common forms of photographic manipulation operation, known as image splicing or image composition is done based on Luminance or the intensity of images. Image splicing is the process that crops and paste regions from the same or separate sources. In this project, I propose a fully automatic image forensic technique to detect digital image forgeries based on exploits inconsistencies in the illumination of images. This approach is machine-learning based and requires minimal user interaction. This technique is applicable to images containing two or more people and requires no expert interaction for the tampering decision. To achieve this, physics-based and statistical-based illuminant estimators are used to incorporate information on the image regions. From these illuminant estimates, texture-based and edge-based features are extracted which are used to provide to a automatic decisions based on machine-learning approach.

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

## I. INTRODUCTION

Detection Digital Image Forgery is a very important field in image processing, because digital images are used in many social areas like in courts when they are used as evidence. In information channels like newspapers, magazines, websites and televisions, digital images are powerful tool for communication. Unfortunately, it is easy to use computer graphics, image editing softwares and image processing techniques to manipulate images.

There are three types of image forgery: Copy-Move image forgery, Image Splicing and Image Retouching. In Copy-Move image forgery, one part of the image is copied and pasted on other part of the same image. In otherwords, the source and destination of the modified image originated from the same image. This is usually done in order to conceal certain details or to duplicate certain aspects of an image.

In Image Splicing, two images are combined to create one-tampered image or it is a technique that involves a composite of two or more images which are combined to create a fake image. In Image Retouching, the images are less modified. It just enhances some features of the image. There are several subtypes of digital image retouching, mainly technical retouching and creative retouching.

In this project, I analyze the digital image splicing detection. Image composition (or splicing) is one of the most common image manipulation operations. It is the process of joint or connect, overlapping and binding their ends. It is a simple process that crops and pastes regions from the same or separate sources. In this paper Luminance used to detect image splicing. Luminance is called as Intensity or value, It is the amount of color or the intensity of the light. It describes the amount of light that passes through or is emitted from a particular area. This approach is fully based on Machine Learning, it is a type of artificial intelligence, process is similar to data mining, Machine Learning focus on prediction based on known properties learned from the trained data. The goal is to devise learning algorithms that do the learning automatically without human intervention or assistance. Texture Descriptor describes a precise statistical distribution of the image texture. That is mainly used for describing the overall structure (appearance) of an image. The Edge descriptor representing the local edge distribution of an 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 viewpoint of a manipulator, proper adjustment of the illumination conditions is hard to achieve when creating a composite image [1]. In this work, make an important step towards minimizing user interaction for an illuminant-based tampering decision-making. I propose a new semiautomatic
method that is also significantly more reliable than earlier approaches. Quantitative evaluation shows that the proposed method achieves a detection rate of 86%, while existing illumination-based work is slightly better than guessing. Then exploit the fact that local illuminant estimates are most

discriminative when comparing objects of the same (or similar) material. 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 this paper, build upon the ideas by [2] and [4]. They use the relatively rich illumination information provided by both physics-based and statistics-based color constancy methods as in [2], [5]. Decisions with respect to the illuminant color estimators are completely taken away from the user, which differentiates this paper from prior work. In Section II, describes present examples of illuminant maps and highlight the challenges in their exploitation. An overview of the proposed methodology, followed by a detailed explanation of all the algorithmic steps is given in Section III. Conclusions and potential future work are outlined in Section IV.

## II. CHALLENGES IN EXPLOITING ILLUMINANT MAPS

To illustrate the challenges of directly exploiting illuminant estimates, I 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 III). 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. Fig.1 shows an example image and its illuminant map, in which an inconsistency can be directly shown: the inserted mandarin orange in the top right exhibits multiple green spots in the illuminant map. All other fruits in the scene show a gradual transition from red to blue. The inserted mandarin orange is the only one that deviates from this pattern.

In practice, however, such analysis is often challenging, as shown in Fig. 2. The top left image is original, while the bottom image is a composite with the right-most girl inserted. Several illuminant estimates are clear outliers, such as the hair of the girl on the left in the bottom image, which is estimated as strongly red illuminated. Thus, from an expert's viewpoint, it is reasonable to discard such regions and to focus on more reliable regions,

Fig1. Example illuminant map that directly shows an inconsistency.

e.g., the faces. In Fig2, however, it is difficult to justify a tampering decision by comparing the color distributions in the facial regions. It is also challenging to argue, based on these illuminant maps, that the right-most girl in the bottom image has been inserted, while, e.g., the right-most boy in the top image is original. 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 recognition scheme operating on illuminant maps.

The features are designed to capture the shape of the superpixels 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.

Fig. 2. Example illuminant maps for an original image (top) and a spliced image (bottom). The illuminant maps are created with the IIC-based illuminan estimator.

## III. OVERVIEW OF PROPOSED METHOD

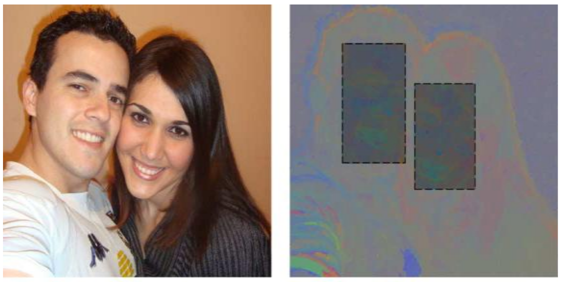
Classify the illumination for each pair of faces in the image as either consistent or inconsistent. Throughout the paper, I can abbreviate illuminant estimation as IE, and illuminant maps as IM. The proposed method consists of five main components: Fig. 4 summarizes these steps.

**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). Use two separate illuminant color estimators: the statistical generalized gray world estimates and the physics-based inverse-intensity chromaticity space, as we explain in the next subsection. We obtain, in total, 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.

*A)Generalized Gray World Estimates:* The classical gray world assumption by Buchsbaum [6] states that the average color of a scene is gray. Thus, a deviation of the average of the image intensities from the expected gray color is due to the illuminant, it has inspired the further design of statistical descriptors for color constancy. Then follow an extension of this idea, the generalized gray world approach by van de Weijer *et al.* [5].

*B)InverseIntensity Chromaticity Estimates:* The second illuminant estimator consider in this paper is called inverse intensity-chromaticity (IIC) space. It was originally proposed by Tan *et al.* [7]. 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.

**2) *Face Extraction:*** This is the only step that may require human interaction. An operator sets a bounding box around each face (e.g., by clicking on two corners of the bounding box) 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, so that only the illuminant estimates of the face regions remain.



(a) (b)

Fig 3: Original image and its gray world map. Highlighted regions in the gray world map show a similar appearance. (a) Original. (b) Gray world with highlighted.

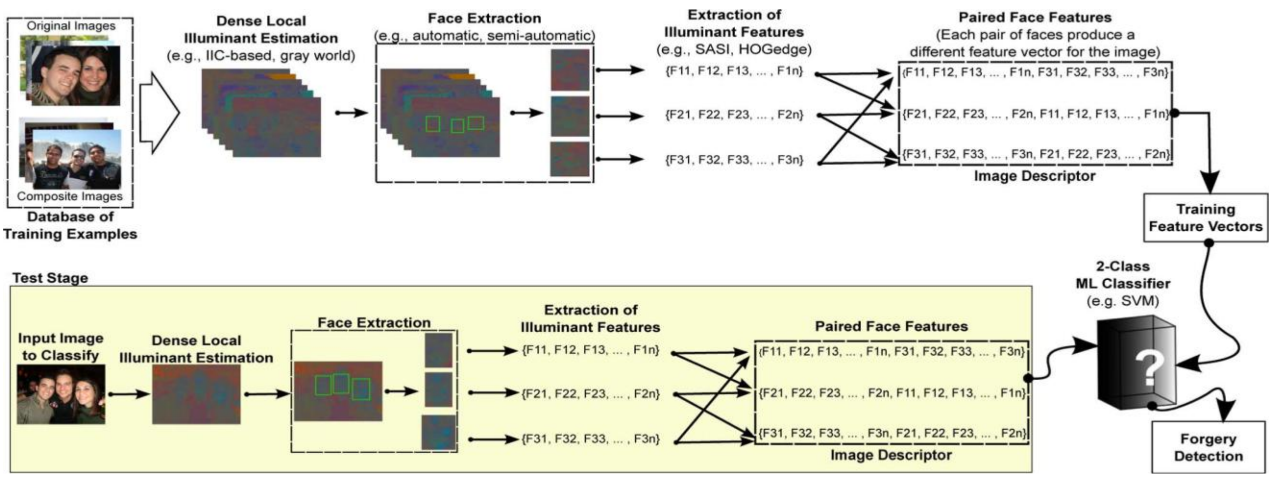



Fig. 4. Overview of the proposed method.

Similar parts, illustrate this setup in Fig. 3. The faces in Fig. 3(a) can be assumed to be exposed to the same illuminant. As Fig. 3(b) shows, the corresponding gray world illuminant map for these two faces also has similar values.

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

*A)SASI Algorithm*: Statistical Analysis of Structural Information (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, refer to [8].

*B)Interpretation of Illuminant Edges: Hogedge Algorithm:* Differing illuminant estimates in neighboring segments can lead to discontinuities in the illuminant map. 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.

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, we first extract edge points using the Canny edge detector [9].
- *Point Description:* We compute Histograms of Oriented Gradients (HOG) [10] to describe the distribution of the selected edge points.
- *Visual Vocabulary:* The number of extracted HOG vectors varies depending on the size and structure of the face under examination. We use visual dictionaries [11] to obtain feature vectors of fixed length.

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

*Face Pair:* To compare two faces, we combine the same descriptors for each of the two faces. For instance, we 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.

**5)** ***Classification:*** Use a machine learning approach to automatically classify the feature vectors. 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, i.e., 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) kernel.

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. Inspired by the work of Ludwig *et al.* [12], use a late fusion technique named SVM-Meta Fusion. It is used to classify each combination of illuminant map and feature type independently using a two-class SVM classifier to obtain the distance between the image's feature vectors and the classifier decision boundary.

## IV. CONCLUSION

In this work, 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. Then treat these illuminant maps as texture maps, also extract information on the distribution of edges on these maps. In order to describe the edge information, propose a new algorithm based on edge-points and the HOG descriptor, called HOGedge.These combines complementary cues (texture- and edge-baed) using machine learning late fusion. The results are encouraging, yielding an AUC of over 86% correct classification. Good results are also achieved over internet images and under cross-database training/testing. Although the proposed method is custom-tailored to detect splicing on images containing faces. The proposed method requires only a minimum amount of human interaction and provides a crisp statement on the authenticity of the image.

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