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Detection of Digital Image Forgeries by Illuminant Color Estimation and Classification

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ABSTRACT: Digital Image forgery is very common nowadays and is done without much difficulty with the help of powerful image editing software's mainly to cover up the truthfulness of the photographs which often serve as evidence in courts. In this paper, we propose a forgery detection method to expose the photographic manipulations known as image composition or splicing by exploiting the color inconsistencies in the illuminated image. For this, effective illuminant estimators are used to obtain illuminant estimates of the image from which texture and edge based features are extracted. The features are used for automatic decision making and finally Extreme Learning machine (ELM) is applied to classify the forged image from the original one.

I.INTRODUCTION

A. IMAGE FORGERIES AND DETECTION

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modelled in the form of multidimensional systems.

Nowadays, 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 not difficult to use computer graphics and image processing techniques to manipulate images. However, before thinking of taking appropriate actions upon a questionable image, one must be able to detect that an image has been altered. Image composition (or splicing) is one of the most common image manipulation operations 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. Thus illuminant color estimates from local image regions are analyzed and illumination map is obtained as a result. 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. Thus, it is preferable to transfer the tampering decision to an objective algorithm. In this work, an important step towards minimizing user interaction for an illuminant-based tampering decision-making is achieved. Hence a new semiautomatic method that is also significantly more reliable than earlier approaches is proposed. Quantitative evaluation shows that the method achieves a detection rate higher than the previous approaches. We exploit the fact that local illuminant estimates are most discriminative when comparing objects of the same (or similar) material. Thus, we 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.

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B.DENSE LOCAL ILLUMINANT ESTIMATION

To compute a dense set of localized illuminant color estimates, the input image is segmented into superpixels, i.e., regions of approximately constant chromaticity.

In this section we define a predicate, D, for evaluating whether or not there is evidence for a boundary between two components in segmentation (two regions of an image). This predicate is based on measuring the dissimilarity between elements along the boundary of the two components relative to a measure of the dissimilarity among neighbouring elements within each of the two components. The resulting predicate compares the inter-component differences to the within component differences and is thereby adaptive with respect to the local characteristics of the data. We define the internal difference of a component $C \leq V$ to be the largest weight in the minimum spanning tree of the component, MST(C,E). That is,

$$\mathrm{Int}(C) = \max_{e \in MST(C,E)} \omega(e) \qquad (1)$$

One intuition underlying this measure is that a given component C only remains connected when edges of weight at least Int(C) are considered. We define the difference between two components $C1,C2 \leq V$ to be the minimum weight edge connecting the two components. That is,

$$\mathrm{Dif}\,(C1,C2) = \min_{vi \in C1, vj \in C2, (vi,vj) \in E} w((vi, vj)) \qquad (2)$$

If there is no edge connecting C1 and C2 we let Dif (C1,C2) = 1. This measure of difference could in principle be problematic, because it reflects only the smallest edge weight between two components. In practice we have found that the measure works quite well in spite of this apparent limitation. Moreover, changing the definition to use the median weight, or some other quantile, in order to make it more robust to outliers, makes the problem of finding a good segmentation NP-hard, as discussed in The region comparison predicate evaluates if there is evidence for a boundary between a pair or components by checking if the difference between the components, Dif (C1,C2), is large relative to the internal difference within at least one of the components, Int(C1) and Int(C2). A threshold function is used to control the degree to which the difference between components must be larger than minimum internal difference.

We define the pairwise comparison predicate as,

$$D(C1,C2) = \mathrm{Dif}\,(C1;C2) > \mathrm{MInt}(C1,C2) \qquad (3)$$

where the minimum internal difference, MInt, is defined as,

$$\mathrm{MInt}(C1,C2) = \min(\mathrm{Int}(C1) + \tau(C1), \mathrm{Int}(C2) + \tau(C2)) \qquad (4)$$

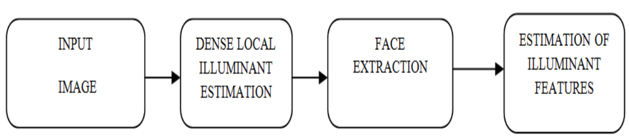

Figure 1. Sequence of steps to extract illuminant features

Per superpixel, the color of the illuminant is estimated. We use two separate illuminant color estimators: the statistical generalized gray world estimates and the physics-based inverse-intensity chromaticity space. 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.

C.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, e.g., the one by Schwartz et *al.*. 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 illuminates 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

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difference in the color of the illuminates is expected. Such differences are hard to distinguish in a fully-automated manner, but can be easily excluded in manual annotation.

D.INTERPRETATION OF ILLUMINANT EDGES: HOGEDGE ALGORITHM

The next step includes Feature extraction .Feature extraction is a special form of reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

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. The full algorithm is described in the remainder of this section. Algorithmic overview of the method is shown later. We 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. The essential thought behind the Histogram of Oriented Gradient descriptors is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The implementation of these descriptors can be achieved by dividing the image into small connected regions, called cells, and for each cell compiling a histogram of gradient directions or edge orientations for the pixels within the cell. The combination of these histograms then represents the descriptor. For improved accuracy, the local histograms can be contrast-normalized by calculating a measure of the intensity across a larger region of the image, called a block, and then using this value to normalize all cells within the block. This normalization results in better invariance to changes in illumination or shadowing.

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II.RELATED WORKS

Illumination-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]. Color-based methods search for inconsistencies in the interactions between object color and light color [2]. Two methods have been proposed that use the direction of the incident light for exposing digital forgeries. Johnson and Farid

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proposed a method which computes a low-dimensional descriptor of the lighting environment in the image plane (i.e., in 2-D). It estimates the illumination direction from the intensity distribution along manually annotated object boundaries of homogeneous color. Kee and Farid extended this approach to exploiting known 3-D surface geometry. In the case of faces, a dense grid of 3-D normals improves the estimate of the illumination direction. To achieve this, a 3-D face model is registered with the 2-D image using manually annotated facial landmarks. Fan *et al.* propose a method for estimating 3-D illumination using shape-from-shading. In contrast to, no 3-D model 3The dataset will be available in full two-megapixel resolution upon the acceptance of the paper. For reference, all images in lower resolution can be viewed at: http://www.ic.unicamp.br/ tjose/files/database-tifs-small-resolution. zip. of the object is required. However, this flexibility comes at the expense of a reduced reliability of the algorithm.In a subsequent extension, Saboia *et al.* automatically classified these images by 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 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. 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.

III.METHODOLOGY

A.SEGMENTATION ALGORITHM

The input is a graph G = (V,E), with n vertices and m edges. The output is a segmentation of V into components S = (C1,............,Cr).

0. Sort E = π(o1,....., om), by non-decreasing edge weight.
1. Start with a segmentation S^0, where each vertex vi is in its own component.
2. Repeat step 3 for q = 1,....,m.
3. Construct S^q given S^{q-1} as follows. Let vi and vj denote the vertices connected by the q-th edge in the ordering, i.e., o_q = (vi, vj). If vi and vj are in disjoint components of S^{q-1} and $w(o_q)$ is small compared to the internal difference of both those components, then merge the two components otherwise do nothing. More formally, let $_{Ci}^{q-1}$ be the component of S^{q-1} containing vi and C_j^{q-1} the component containing vj .
If $C_i^{q-1} \neq C_j^{q-1}$ and $w(o_q) \leq MInt(C_i^{q-1}, C_j^{q-1})$ then S^q is obtained from S^{q-1} by merging C_i^{q-1} and C_j^q-1. Otherwise $S^q=S^{q-1}$
4. Return S = S^m.

IV.SIMULATION RESULTS

Figure 2. Input image

This is the input image chosen for segmentation

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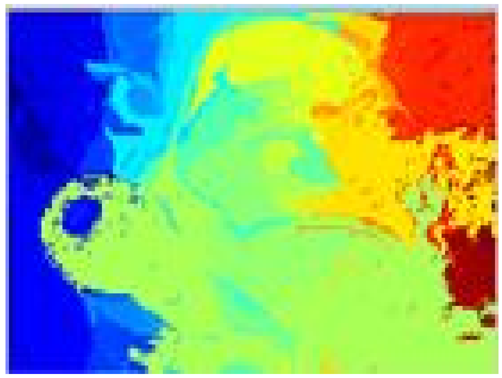

Figure 3. Segmentation image

The input image is segmented using efficient graph edge based algorithm.

Figure 4. Bounding box crop image

Face extraction is done using bounding box automated algorithm.

Figure 5. Gray edge image

The above image is obtained using gray edge hypothesis.

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Figure 6. Gray world image

Statistical generalized gray world estimate is used to obtain the above image.

Figure 7. Inverse intensity chromaticity image

The figure exhibits the result above when physics based inverse intensity chromaticity estimate is done in input image. HOG feature values H2 from segmented image are obtained as

0.2404

0.3682

0.3717

0.2383

0.2623

0.2901

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V.CONCLUSION

In this project work, a new method for detecting forged images using illuminant color estimator has been proposed. In the first phase, the illuminant color using a statistical gray edge method and physics based method which exploits the inverse intensity chromaticity color space is estimated and also information is extracted on the distribution of edges on the illuminant maps. In order to describe the edge information, an algorithm based on edge-points and the Histogram Of Oriented Gradients (HOG) descriptor called HOG edge algorithm is applied. The segmented feature values are estimated using this algorithm. This project can be further developed by extracting both edges and textures of forged image and pairing the face features for the classification. This would be obtained using ELM classifier.

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