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Illuminant maps analysis for image splicing detection

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Introduction

Digital images are easy to manipulate thanks to the availability of the **powerful editing software** and **sophisticated digital cameras**.

The development of methods for verifying **image authenticity** is a real need in forensics.

Purpose: to detect image splicing aimed at *deceiving* the viewer.

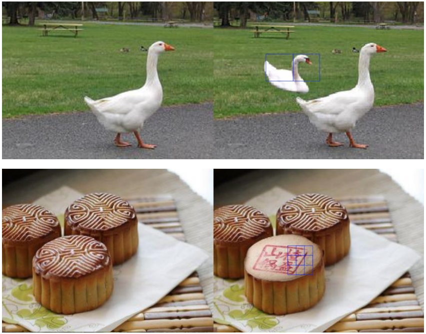
Forgery detection

Image splicing detection techniques are based on *inconsistencies*:

1. **Image resampling, copy-paste**: deduced from image metadata.
2. **Compression-based inconsistencies**: JPEG compression introduces blocking artifacts. Manufacturers of digital cameras and image processing software typically use different JPEG quantization tables.
3. **Neighboring pixels relationship inconsistencies**: when an image is spliced some artifacts can be created.
4. **Intrinsic image properties inconsistencies**: e.g. scene lights, shadows or perspective.

Lighting-based inconsistencies

Methods based on **lighting inconsistencies** are particularly *robust*: a perfect illumination adjustment in a image composition is very hard to achieve.



Lighting-based inconsistencies

These methods can be divided into two types of approaches:

1. **Object light source inconsistencies**: detected using *shadows*, *face geometry*, *generic object surfaces*.
2. **Illuminant colors inconsistencies**: assuming that a scene is lit by the same light source, all objects must have the same illuminant colors.
   2.1 *Specular dichromatic reflectance models*
   2.2 *Illuminant Maps (IMs)*

Illuminant Maps estimation

For the Illuminant Maps estimation, two different techniques are used:

1. A *statistical-based* approach using **Generalized Grayworld Estimate (GGE)** algorithm.
2. A *physics-based* approach using **Inverse-Intensity Chromaticity (IIC)** method.

Image

Illuminant map

Distance map

Generalized Greyworld Estimate (GGE)

Generalized Greyworld Estimate is proposed in [2] as a combination of the *Grey-World* and *Grey-Edge methods* aimed to evaluate **color constancy**.

The main premise behind it is that in a normal well color balanced photo, the **average** of all the colors is a neutral gray. Therefore, it assumes that the *Minkowski norm* of the derivative of the reflectance in a scene is **achromatic**.

$$k\mathbf{e}^{n,p,\sigma} = \left(\int \left|\frac{\vartheta^n \mathbf{f}^\sigma(\mathbf{x})}{\vartheta \mathbf{x}^n}\right|^p d\mathbf{x}\right)^{\frac{1}{p}} \tag{1}$$

where $\mathbf{x}$ denotes a pixel coordinate, k is a scale factor, $|\cdot|$ is the absolute value operator, ϑ the partial differential operator, $\mathbf{f}^\sigma$ is the observed intensities at position $\mathbf{x}$, smoothed by a Gaussian kernel σ, p is the *Minkowski norm*, and n is the derivative order.

Generalized Greyworld Estimate (GGE)

The illuminant estimation of (1) is a framework for low-level based illuminant estimation based on three variables:

1. The order n of the image structure.
2. The Minkowski norm p which determines the relative weights of the multiple measurements from which the final illuminant color is estimated.
3. The scale of the local measurements as denoted by σ.

Advantages:

- the Minkowski norm of RGB values or derivatives can be computed *extremely fast*
- the method does not require an image database taken under a **known light source**

Inverse-Intensity Chromaticity (IIC)

Extension of the **dichromatic reflectance model**, which states that *the amount of light reflected from a point,* $\mathbf{x}$*, of a dielectric, non-uniform material is a linear combination of diffuse reflection and specular reflection*.

Given an image taken with a **RGB camera**, the response $I_c(\mathbf{x})$ for each color filter $c \in \{R, G, B\}$ is

$$I_c(\mathbf{x}) = m_d(\mathbf{x})B_c(\mathbf{x}) + m_s(\mathbf{x})G_c(\mathbf{x})$$

where m_d and m_s are geometric parameters of **diffuse and specular reflection**.

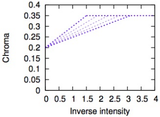
Let $\Delta_c(\mathbf{x})$ and $\Gamma_c(\mathbf{x})$ be the diffuse and **specular chromaticity**:
$\Delta_c(\mathbf{x}) = \frac{B_c(\mathbf{x})}{\sum_{iin\{R,G,B\}} B_i(\mathbf{x})}$ and $\Gamma_c(\mathbf{x}) = \frac{G_c(\mathbf{x})}{\sum_{iin\{R,G,B\}} G_i(\mathbf{x})}$

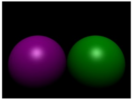
Inverse-Intensity Chromaticity (IIC)

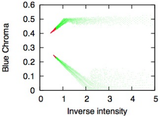
In this model, the intensity $I_c(\mathbf{x})$ and the chromaticity $\sigma_c(\mathbf{x})$ of a color channel $c \in \{R, G, B\}$ at pixel position $\mathbf{x}$ are related by

$$\sigma_c(\mathbf{x}) = p_c(\mathbf{x}) \frac{1}{\sum_{i \in \{R,G,B\}} I_i(\mathbf{x})} + \Gamma_c(\mathbf{x}) \tag{2}$$

where $p_c(\mathbf{x}) = w_d(\mathbf{x}) \sum_i B_i(\mathbf{x})(\Delta_c(\mathbf{x}) - \Gamma_c(\mathbf{x}))$





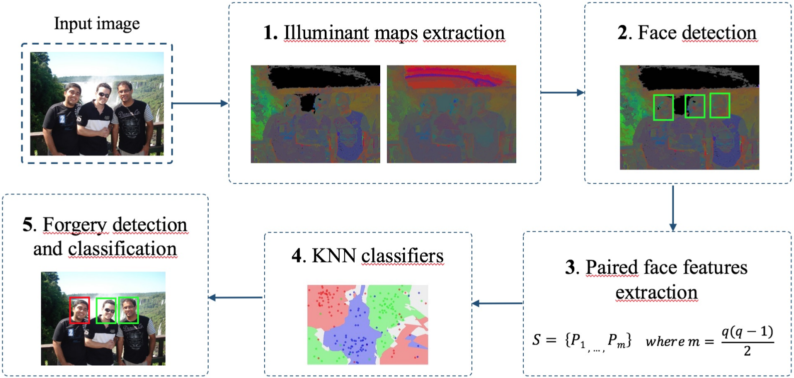


The *domain* of the line is determined by $\frac{1}{\sum_i I_i(\mathbf{x})}$ and the *range* is given by $0 \leq \sigma_c \leq 1$. Domain and range together form the **inverse-intensity chromaticity (IIC) space**.

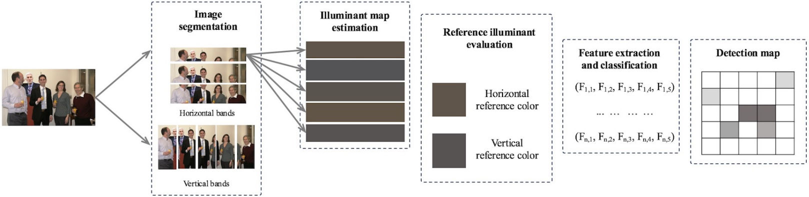
Proposed approach

- **Face forgery detection module**: specifically for detecting forgeries involving people. Based on the work presented by Carvalho et al. [1].
- **Regional forgery detection module**: image content independent. Based on the work presented by Fan et al. [2]

Face forgery detection module



Region forgery detection module



Experimental results - 1

Test case	Train	Test	Accuracy	AUC	F-Score
Test 1	DSO-1	DSO-1	0.84	0.90	0.78
Test 2	DSI-1	DSI-1	0.89	0.92	0.89
Test 3	DSO-1	DSI-1	0.59	0.58	0.64
Test 4	DSI-1	DSO-1	0.63	0.60	0.54

Tabella : Performance of face forgery detection module over paired faces using non-uniform weights.

Experimental results - 1

Test case	Train	RC	ACC	AUC	F-Score
Test 1	-	Median	0.49	0.32	0.25
Test 2	-	Global	0.52	0.40	0.27
Test 3	SplicedCC	Median	0.54	0.53	0.26
Test 4	SplicedCC	Global	0.57	0.57	0.31
Test 5	SplicedDSO	Median	0.53	0.50	0.27
Test 6	SplicedDSO	Global	0.61	0.63	0.33

Tabella : Performance of region forgery detection module.

Conclusions

- Two different approaches for forgery detection are presented: a face forgery detection module and a generic region forgery detection module.
- *Illuminant maps* are used to entail the interaction between the light source and the objects contained in a scene.
- Face module achieved most promising results, but it needs some *a priori* knowledge about the content of the image.
- **Future developments**: given that our method compares skin material, it is feasible to use additional body parts, such as arms and legs, to increase the detection and confidence of the method.
- Further improvements can be achieved when more advanced illuminant color estimators become available.

References

[1] T. Carvalho, et al. *Illuminant-Based Transformed Spaces for Image Forensics*. IEEE Transactions on Information Forensics and Security 11.4 (2016): 720-733.

[2] Y. Fan, P. Carrè, and C. Fernandez Maloigne. Image splicing detection with local illumination estimation. In Image Processing ICIP, 2015.

[3] J. van de Weijer, Th. Gevers, A. Gijsenij, Edge-Based Color Constancy, IEEE Trans. Image Processing, accepted 2007.

[4] C. Riess and E. Angelopoulou. 2010. *Scene illumination as an indicator of image manipulation*. In *Proceedings of the 12th international conference on Information hiding*, Berlin, Heidelberg, 66-80.