UNIVERSITÀ DEGLI STUDI FIRENZE

Scuola di Ingegneria
Corso di Laurea Magistrale in Ingegneria Informatica

An illuminant estimation method for image splicing detection

Lorenzo Cioni

Anno Accademico 2015/2016

Introduction

This method is based on *T. Carvalho*, *V. Schetinger et al.* works presented in [1] and [2].

Mail goal: finding image inconsistencies based on **illuminant estimation** in order to determine if an image has been **tampered** or not.

The proposed method

The method consists on 4 steps:

1. **Region of Interest (ROI)** definition: manual
2. **Illuminant Map** estimation
    2.1 *Generalized Greyworld Estimate* (**GGE**): statistic-based
    2.2 *Inverse-Intensity Chromaticity* (**IIC**): physics-based
3. **Statistical difference** between the IMs
4. Image **descriptor**: based on IMs
5. **Classification** of ROIs

1. Region of Interest definition

The method proposed by Carvalho et al. [1] is restricted to images containing at least two faces. This method is able to classify as fake **any single ROIs** defined in the image. User can **manually select** suspicious image regions.

2. 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.

2.1 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.

2.1 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**

2.2 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**.

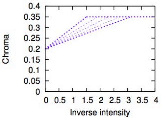
Let $\Delta_c(\mathbf{x})$ and $\Gamma_c(\mathbf{x})$ be the diffuse and **specular chromaticity**:
$\Delta_c(\mathbf{x}) = \frac{B_c(\mathbf{x})}{\sum_{iin\{R,G,B\}} B_i(\mathbf{x})}$ and $\Gamma_c(\mathbf{x}) = \frac{G_c(\mathbf{x})}{\sum_{iin\{R,G,B\}} G_i(\mathbf{x})}$

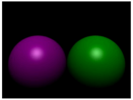
2.2 Inverse-Intensity Chromaticity (IIC)

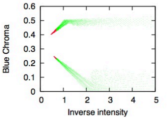
In this model, the intensity $I_c(\mathbf{x})$ and the chromaticity $\sigma_c(\mathbf{x})$ of a color channel $c \in \{R, G, B\}$ at pixel position $\mathbf{x}$ are related by

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

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



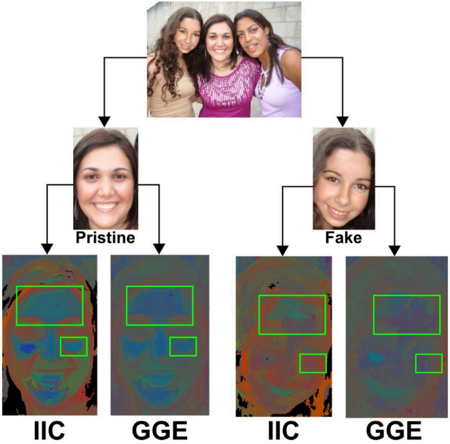




The *domain* of the line is determined by $\frac{1}{\sum_i I_i(\mathbf{x})}$ and the *range* is given by $0 \leq \sigma_c \leq 1$. Domain and range together form the **inverse-intensity chromaticity (IIC) space**.

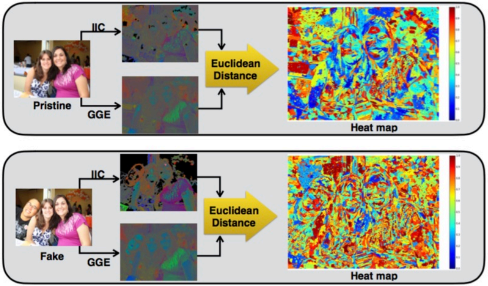
3. Statistical difference

The GGE and IIC methods produce **Illuminant Maps** with different aspects for the same image.



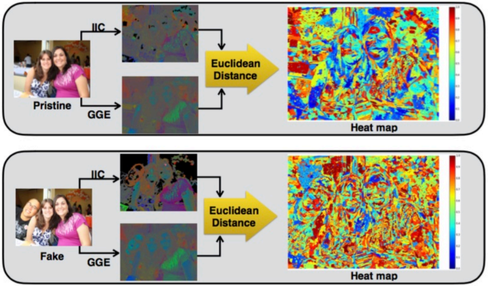
3. Statistical difference

The appearance in terms of colors in IMs generated for *pristine faces* are very similar in GGE and IIC. But, when an image contains a **fake face**, the *difference* (in terms of color appearance) *between GGE and IIC for this fake face is increased*.



3. Statistical difference

The heat maps highlight that **pristine images** produce a map where **shades of blue are dominants**, pointing to a *lower difference between IIC and GGE maps*. **Fake images** produce a heat map where **shades of red are dominant**, indicating a *more significant difference*.



3. Statistical difference

Given an image with q **ROI** the **signature** generated by this image can be defined by

$$\vartheta = \frac{1}{q} \sum_{i=1}^{q} \log(\|\lambda_n(g_{GGE})^2 - \lambda_n(f_{IIC})^2\|) \tag{3}$$

where $\lambda_n(f_{GGE})$ and $\lambda_n(f_{IIC})$ are the n-th higher eigenvalue

extracted from the i-th ROI into the GGE and IIC representations.

4. Image descriptor

In order to *eliminate the multiple ROI dependency*, a **single descriptor** combining multiple extracted eigenvalues is built:

$$D = \{\mu_1, \mu_2, \ldots, \mu_{n-1}, \mu_n\} \tag{4}$$

where μ_i is the difference metric based on the *i*-th higher eigenvalue extracted from one ROI. In this way, **individual ROI** can be classified as fake or pristine.

4. Image descriptor

A set of difference metrics are taken into account in order to measure the difference bewtween ROIs

Difference Metric	Formula
Linear	$\mu_n = \lambda_n(f_{GGE}) - \lambda_n(f_{IIC})$
Quadratic	$\mu_n = (\lambda_n(f_{GGE}) - \lambda_n(f_{IIC}))^2$
Logarithmic	$\mu_n = log\|\|\lambda_n(f_{GGE}) - \lambda_n(f_{IIC}\|\|$
Square Root	$\mu_n = \sqrt[2]{(\|\|\lambda_n(f_{GGE}) - \lambda_n(f_{IIC})\|\|)}$
Cubic Root	$\mu_n = \sqrt[3]{(\lambda_n(f_{GGE}) - \lambda_n(f_{IIC}))}$

5. Classification

The classification task is performed using a **SVM classifier**. The SVM parameters are tuned with the *10-fold cross-validation* techique maximizing the **accuracy** obtained in cross-validated data.

Difference Metric	Accuracy
Linear	0.72
Quadratic	0.67
Logarithmic	0.80
Square Root	0.73
Cubic Root	0.81

Future works

- **Replicate** the algorithm and perform it on a different dataset (translate code in Python/C++)
- Use a simple **sliding window** over the whole image with different size and scale and perform the algorithm.
- Use a **different classifier** in the classification step (*KNN*, *NN*, *etc.*).
- Exploring different **distance metrics**.

Riferimenti bibliografici

[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] V. Schetinger et al. *Exploring Statistical Differences Between Illuminant Estimation Methods for Exposing Digital Forgeries*; 2016.

[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.