UNIVERSITÀ
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SCUOLA DI INGEGNERIA
Corso di Laurea Magistrale in Ingegneria Informatica

Illuminant map 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**.

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

Forgery detection approaches

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2. **Scene level**: exploiting inconsistencies in scene shadows, lights, reflections, perspective, and geometry of objects.

Main advantage: being fairly independent on low-level characteristics of images, they are extremely robust to compression, altering, and other image processing operations

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2. **Illuminant colors inconsistencies**
   2.1 *Specular dichromatic reflectance models* (Gholap and Bora, 2008 [5])
   2.2 **Illuminant Maps (IMs)**

Illuminant Maps estimation

For the *Illuminant Maps* estimation, two different *state-of-art* techniques are used:

1. A *statistical-based* approach using **Generalized Grayworld Estimate (GGE)** algorithm (Van de Weijer *et al.*, 2007 [3]). Rely on hypotheses related to statistics of image pixels (e.g. the *gray world assumption*).

2. A *physics-based* approach using **Inverse-Intensity Chromaticity (IIC)** method (Riess and Angelopoulou, 2010 [4]). Rely on theoretical formulations of how light interacts with objects (e.g. *the dichromatic reflectance model*)

Image

Illuminant map

Proposed approach

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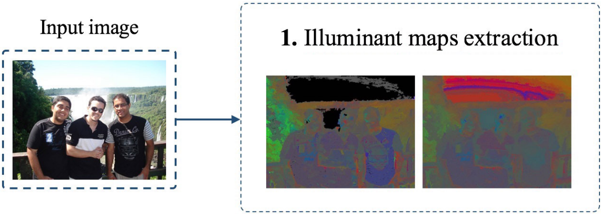
- **Face forgery detection module**: specifically for detecting forgeries involving people. Based on the work presented by Carvalho *et al.* 2016 [1]. Improving and automating the detection process.
- **Regional forgery detection module**: image content independent. Based on the work presented by Fan *et al.* in 2015 [2]. A more general and experimental approach.

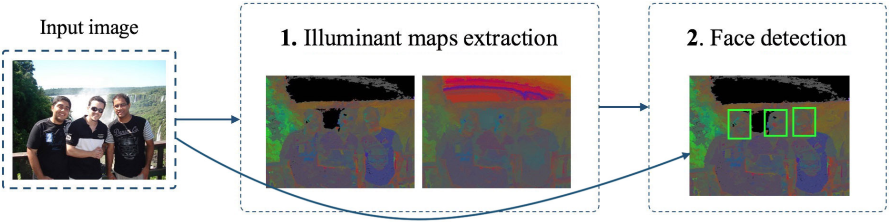
Face forgery detection module - 1

Input image

Face forgery detection module - 1



Face forgery detection module - 1



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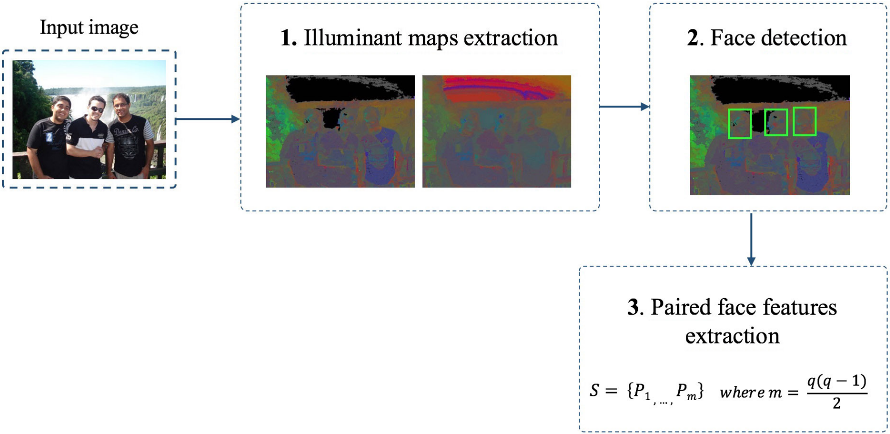

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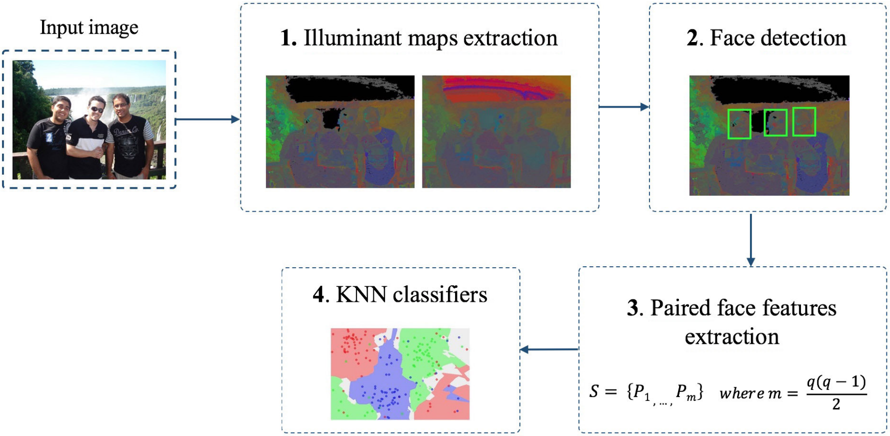

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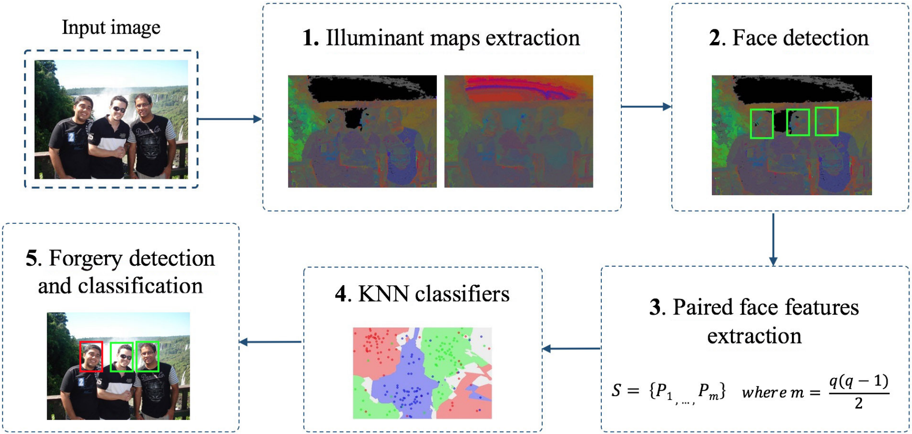
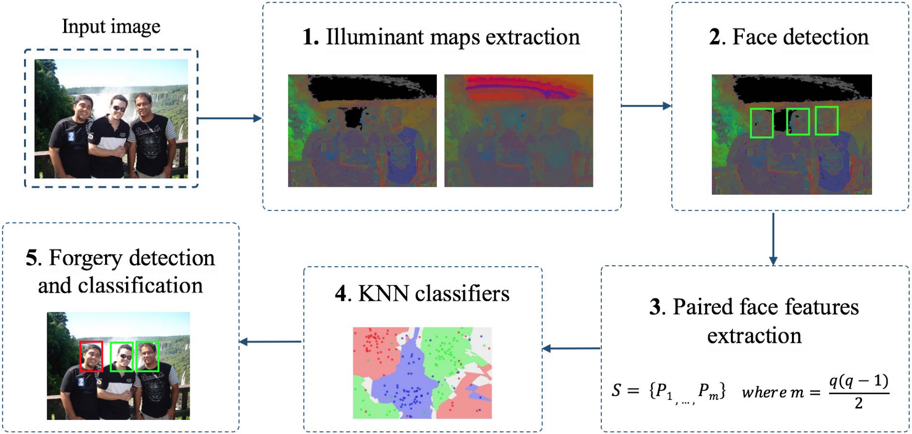


Face forgery detection module - 1

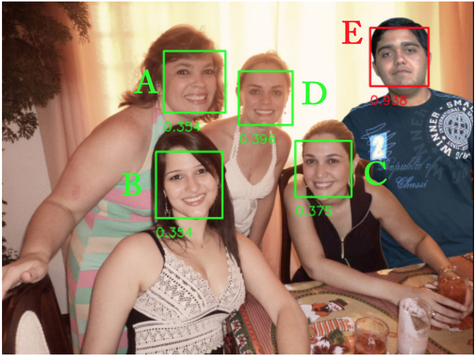


Introducing a *face detector* and *soft classification scores*.

Face forgery detection module - 2

The output of the algorithm consist in a **forgery score** for each detected face.

Face	Score
A	0.354
B	0.354
C	0.375
D	0.396
E	**0.936**



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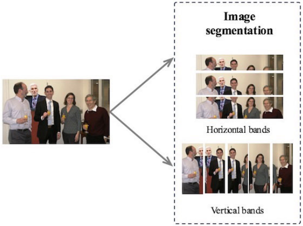

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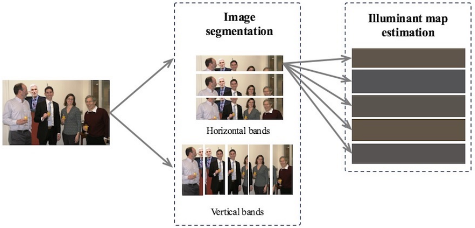

GGE estimation $$ke^{n,p,\sigma} = \left(\int \left|\frac{\vartheta^n \mathbf{f}^\sigma(\mathbf{x})}{\vartheta \mathbf{x}^n}\right|^p d\mathbf{x}\right)^{\frac{1}{p}}$$

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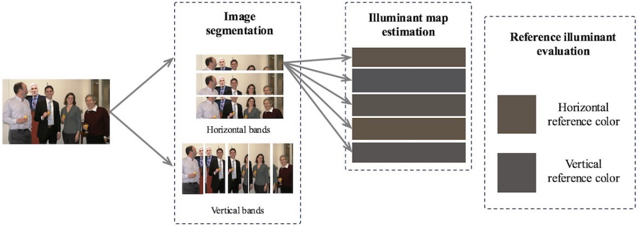

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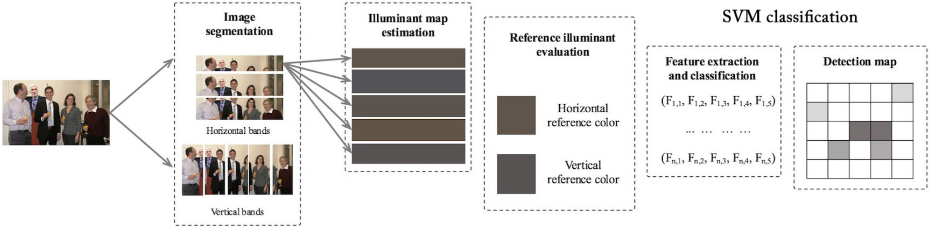

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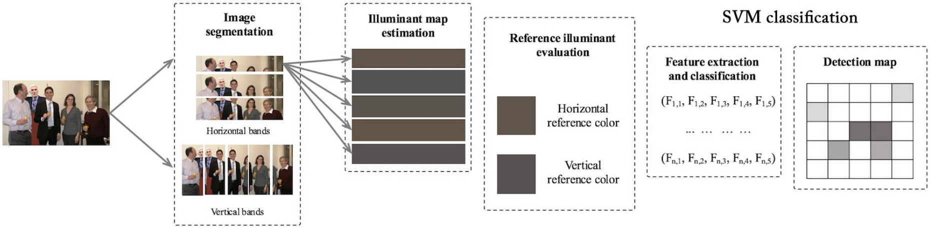

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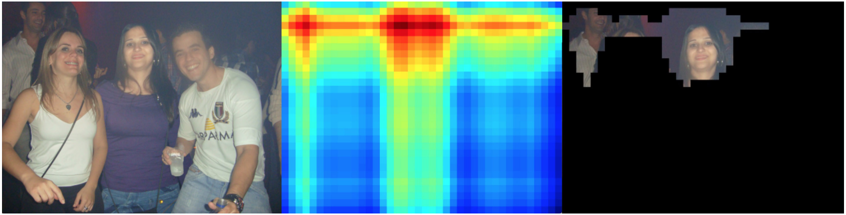
Two different **reference colors** are considered:

- *Median*: the median illuminant color for each direction
- *Global*: the whole image illuminant color

Regional forgery detection module - 2

The output of the algorithm consist in the forgery **regional mask**.



Work best in presence of **uniform backgrounds colors** and simple light settings.

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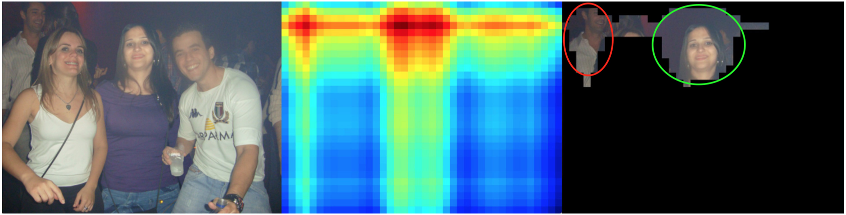

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Evaluation datasets

- **DSO-1**: 200 indoor and outdoor images (100 original and 100 doctored) with an image resolution of 2048 x 1536 pixels.
- **DSI-1**: 50 downloaded images (25 original and 25 doctored) with different resolutions. Original images are downloaded from *Flickr*, doctored images collected from different websites.

Figura : DSO-1 sample spliced image

Figura : DSI-1 sample spliced image

Experimental results - 1

Experimental results for face forgery detection module.

N.	Train	Test	Faces	Accuracy	F-Score
1	DSO-1	DSO-1	540	0.81	0.64
2	DSI-1	DSI-1	133	0.75	0.66
3	DSO-1	DSI-1	540	0.63	0.25
4	DSI-1	DSO-1	130	0.67	0.37

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

Good results in **cross-validation** evaluations. In a cross dataset approach, the dataset used for training makes the difference.

Experimental results - 2

Experimental results for regional forgery detection module.

Test case	Train	RC	ACC	AUC	F-Score
Test 1	SplicedCC	Median	0.54	0.53	0.26
Test 2	SplicedCC	Global	0.57	0.57	0.31
Test 3	SplicedDSO	Median	0.53	0.50	0.27
Test 4	SplicedDSO	Global	0.61	0.63	0.33

Tabella : Performance of region forgery detection module

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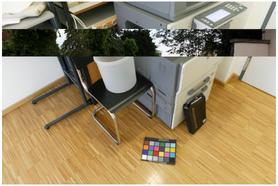

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Better results achieved using the **global illuminant color** as reference.

Very low accuracy: not suitable for a forensic approach.

Conclusions

- Two different approaches for forgery detection are presented: a face forgery detection module and a generic region forgery detection module.
- Face module achieved most promising results, but it works only with images involving people forgeries.
- **Future developments**: extend the approach to generic objects with composed by similar material.
- 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.

[5] S. Gholap and P. Bora. *Illuminant colour based image forensics.* In TENCON IEEE 2008.

[6] G. Buchsbaum. *A spatial processor model for object colour perception*. Journal of the Franklin Institute, 1980.