Asplund's Metrics Useful for Images Acquired under Variable Lighting

Michel Jourlin

Laboratoire Hubert Curien, UMR CNRS 5516, Saint-Etienne University (France)

Asplund's Metrics Useful for Images Acquired under Variable Lighting

- Images acquired under unstable lighting conditions are very difficult to process
- For example, such a situation occurs for video-surveillance images of streets, highways, military or industrial sensitive sites, aerial or submarine images …

  and also :
- Images acquired “in transmission” (observed object between the source and the sensor) : microscopy, tomography, radiography, scanner…, in which the opacity and the thickness of the object may be variable.

Asplund's Metrics Useful for Images Acquired under Variable Lighting

- In order to overcome the drawbacks generated by a variable lighting, we propose to develop our image processing algorithms inside the

LIP (Logarithmic Image Processing) framework

- We will see that such a framework permits to develop tools and algorithms presenting a lot of significant advantages compared to the « classical » ones

Ref: M. Jourlin (2016), « Logarithmic Image Processing : Theory and Applications », *Advances in Imaging and Electron Physics*, Vol 195, *Academic Press*, 259 p.

Asplund's Metrics Useful for Images Acquired under Variable Lighting

- The most significant properties of the LIP Model:
  - It is based on the « Transmittance Law », which gives it a ***strong physical justification***
  - The laws defined inside the Model (addition of two images and homothety of an image) possess ***strong mathematical properties*** due to the fact they give a ***Vector Space*** structure to the space of images
  - Moreover, Brailean (°) has established that the Model is ***consistent with the Human Visual System***

(°) J. Brailean, B. Sullivan, C. Chen, M. Giger, (1991), "Evaluating the em algorithm using a human visual fidelity criterion", *Int. Conf. on Acoustics. Speech and Signal Processing*, 2957–2960

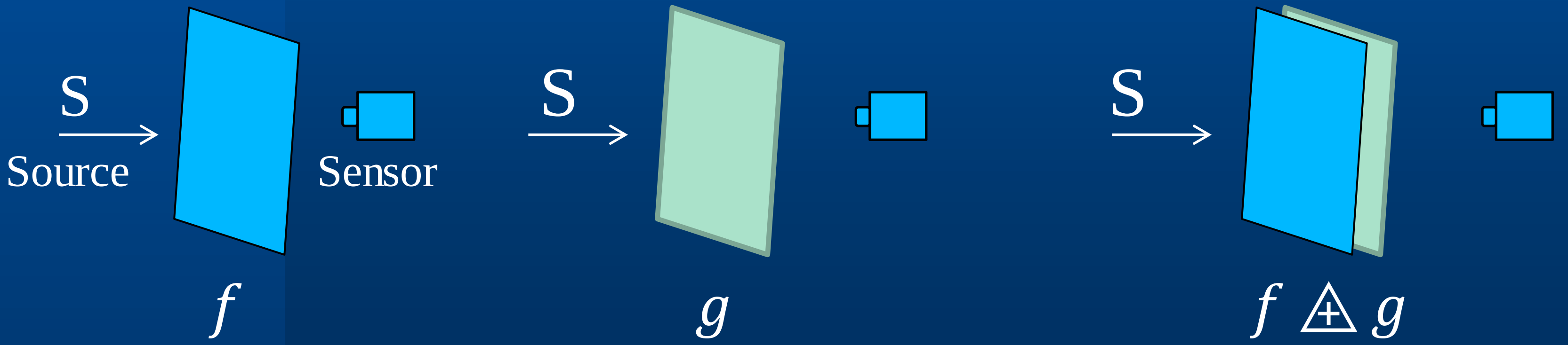
Recalls on the LIP Model

Notations: A grey level image is a function defined on the spatial domain D with values in the grey scale $[0, M[$:

$$f : D \subset \mathbb{R}^2 \rightarrow [0, M[\subset \mathbb{R}$$

- Definition of the Logarithmic Addition Law

The addition $f \triangle\!\!\!\!+\, g$ of two images f and g is interpretable (for images acquired in transmission) as the superimposition of the obstacles (objects) generating respectively f and g.



Recalls on the LIP Model

- Definition of the Logarithmic Addition Law
  - It has been established that

$$f \triangle\!\!\!\!+ \, g = f + g - \frac{f.g}{M} \qquad (1)$$

Remark : the opposite of f and the subtraction of f and g have also been defined according to the formulas:

$$\triangle\!\!\!\!- \, f = \frac{-f}{1-\frac{f}{M}} \quad \text{and} \quad f \triangle\!\!\!\!- \, g = \frac{f-g}{1-\frac{g}{M}} \qquad (2)$$

Warning : *within the LIP model,* 0 *corresponds to the "white" extremity of the grey scale*, which means to the source intensity, i.e. when no obstacle (object) is placed between the source and the sensor.

The other extremity M is a limit situation where no element of the source is transmitted (black value). For 8-bits images, $M = 2^8 = 256$

Recalls on the LIP Model

Variation of the source intensity

An image f represented in the scale $[0, M[$ becomes $f \,{\triangle\!\!\!\!+}\, C$ in the scale $[C, M[$, which corresponds to an attenuation of f

$\Rightarrow$ on the opposite,
0 appears as a « negative » grey level related to $[C, M[$ and
negative grey levels appear as light intensifiers

Recalls on the LIP Model

- Definition of the Logarithmic Scalar Multiplication
  - For every $\lambda \in \mathbb{R}$

$$\lambda \triangle\!\!\!\times f = M - M\left(1 - \frac{f}{M}\right)^{\lambda} \qquad (3)$$

Remark: such a multiplication consists of **stacking f upon itself λ times** ⇨ the resulting image is darker (resp. brighter) than f when $\lambda > 1$ (resp. $\lambda < 1$) and obviously unchanged when $\lambda = 1$

To conclude these recalls, the two laws $\triangle\!\!\!+$ *and* $\triangle\!\!\!\times$ equip the space of grey level functions with a *Vector Space* structure, which gives access to a countless set of tools and concepts available in this kind of spaces (for example the logarithmic interpolation between two images or the scalar product of two images, which represents in fact a correlation coefficient between them).

What can we expect from the LIP framework ?

- We can define new notions of contrast, physically founded and interpretable:
  - The Logarithmic Additive Contrast between two points (x, y):

$$C^{\triangle\!\!\!+}_{(x,y)}(f) = Max\big(f(x), f(y)\big) \triangle Min\big(f(x), f(y)\big) \qquad (4)$$

Such a contrast represents the grey level we must add to the brightest pixel ($Min\big(f(x), f(y)\big)$ to get the darkest one ($Max\big(f(x), f(y)\big)$.

Using the subtraction formula (2) yields to the explicit expression:

$$C^{\triangle\!\!\!+}_{(x,y)}(f) = \frac{|f(x) - f(y)|}{1 - \frac{Min(f(x), f(y))}{M}} \qquad (5)$$

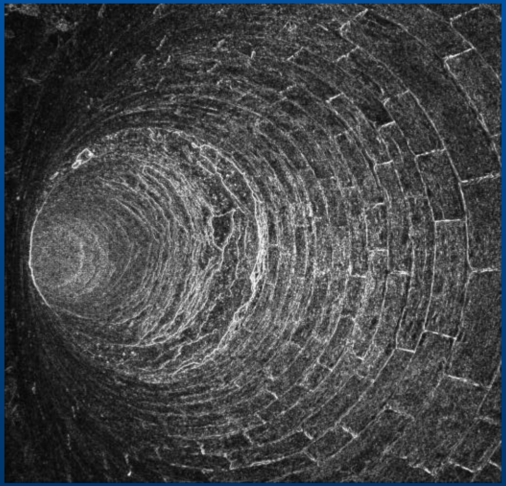
What can we expect from the LIP framework ?

Contour detection:

We can compute the LIP contrast between a pixel x and each of its 8 neighbors and affect to x the maximal one:

Initial image of a well

Contour detection (classical Sobel)



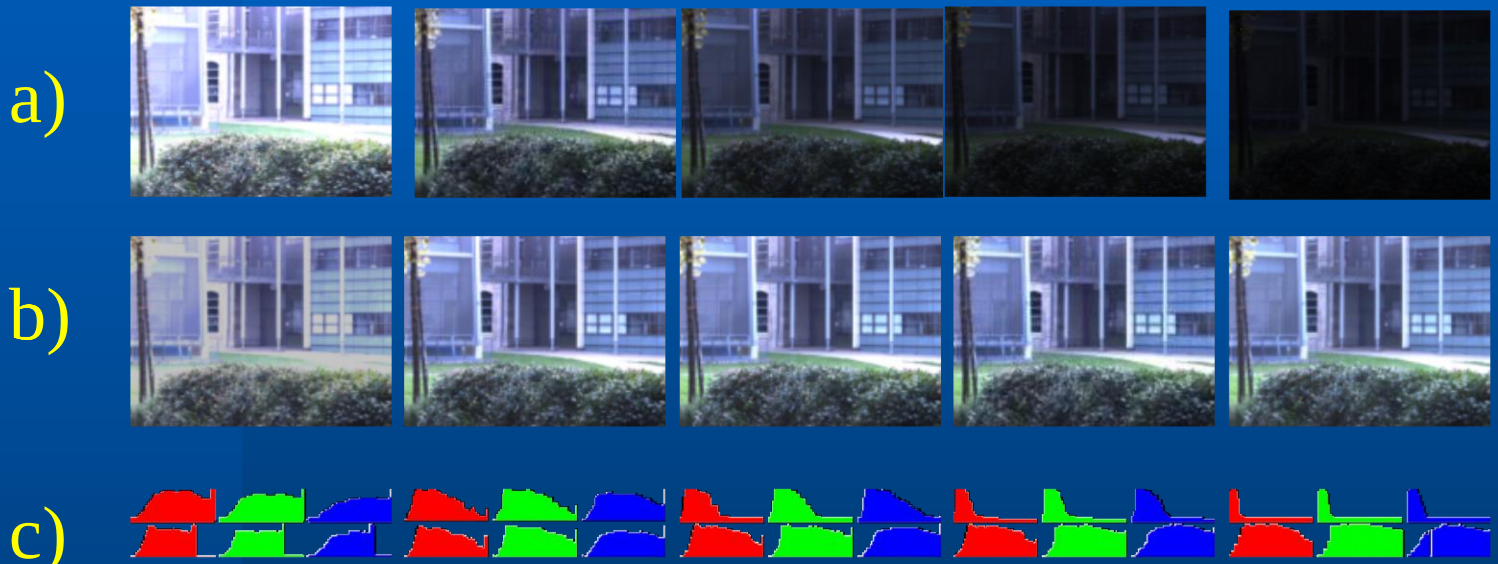
Contour detection (LIP contrast)

What can we expect from the LIP framework ?

Image enhancement: when we subtract (resp. add) a constant (i.e. a grey level) to an image in the LIP sense, we brighten (resp. darken) it

What can we expect from the LIP framework ?

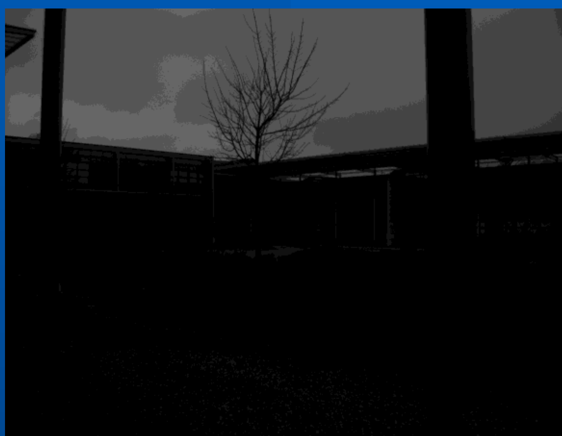
Image stabilization (may be done at camera speed of 25 im./s)



a) Variable lighting
b) Stabilized images
c) Corresponding histograms

What can we expect from the LIP framework ?

Exposure time simulation (LIP addition/subtraction of a constant)



a)

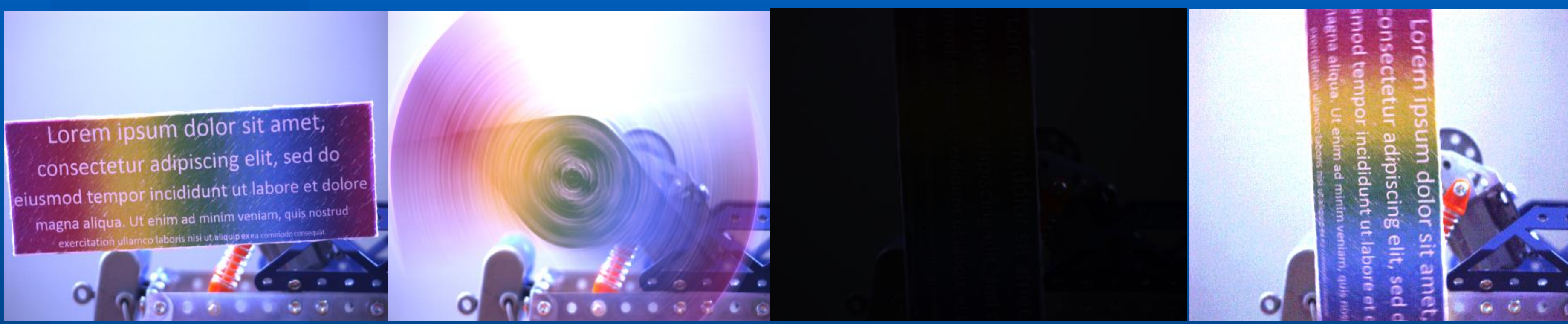
b)

c)

a) Image f: "Laboratory" acquired with exposure time = 10ms
b) Image g: "Laboratory" acquired with exposure time = 100ms
c) Starting from a), simulation of an exposure time of 100ms

What can we expect from the LIP framework ?

Exposure time simulation



a) *b)* *c)* *d)*

a) Label acquired at 30ms (motionless wheel)
b) Label acquired at 30ms (wheel rotating at 6.4 revolutions per second)
c) Rotating label acquired at 1ms
d) Simulation of an exposure time of 30ms starting from image c)

What can we expect from the LIP framework ?

Texture evaluation independently of the lighting


a)


b)


c)

a) Initial image
b) LIP additive maximal contrast applied to a)
c) Sobel operator applied to a)

What can we expect from the LIP framework ?

Defining novel metrics (distances between images)

Let us recall formula (4):

$$C^{\triangle\!\!\!\!+}_{(x,y)}(f) = Max\big(f(x), f(y)\big) \triangle\!\!\!\!- \; Min\big(f(x), f(y)\big)$$

defining the Logarithmic Additive Contrast between two points x and y of an image f

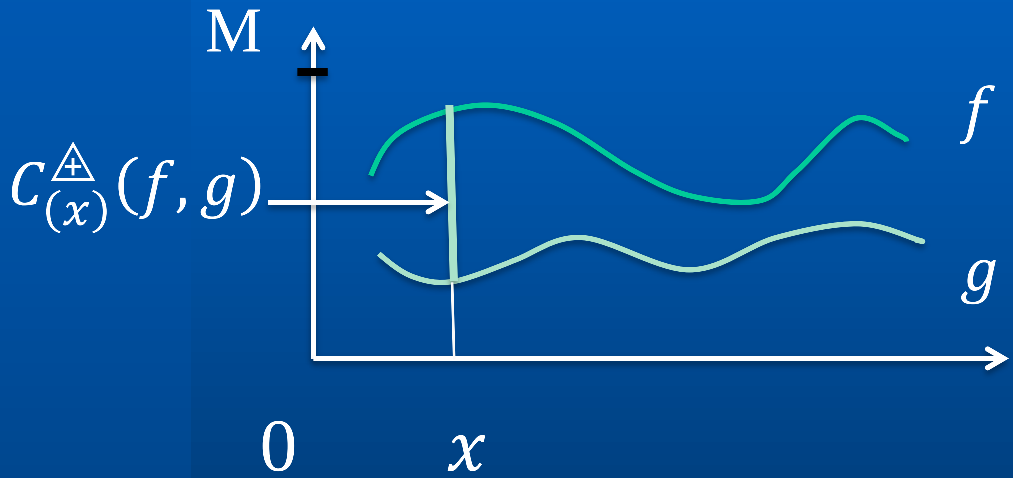
In the same way, we can compute the Logarithmic Additive Contrast between two images f and g at the same point x according to:

$$C^{\triangle\!\!\!\!+}_{(x)}(f, g) = Max\big(f(x), g(x)\big) \triangle\!\!\!\!- \; Min\big(f(x), g(x)\big) \quad (6)$$

This is the first step for defining a novel distance between f and g

What can we expect from the LIP framework ?

Defining novel metrics (distances between images)



In fact, we can get a Logarithmic distance between f and g on a ROI by computing the average value or the maximal value of $C_{(x)}^{\triangle\!\!\!\!+}(f,g)$ when x varies in the ROI.

What can we expect from the LIP framework ?

Defining novel metrics (distances between images)

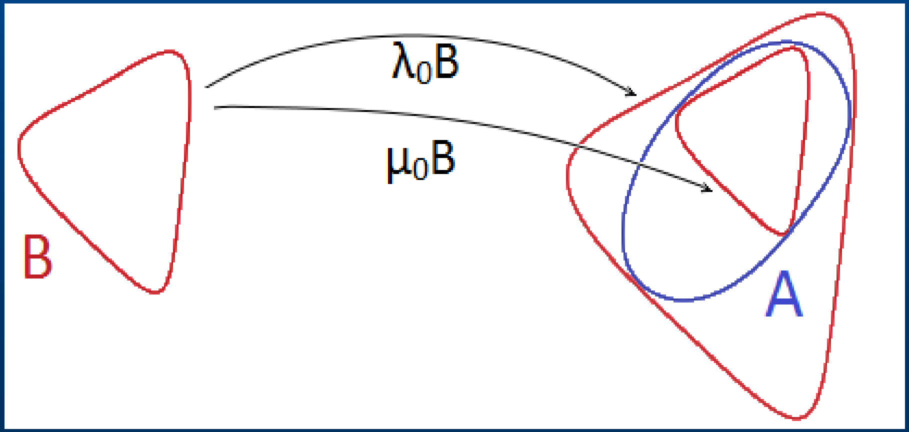
Another approach consists of starting from a little known metric defined on binary shapes: the Asplund's metric

A and B being two binary shapes, Asplund proposed to perform a double probing of one shape (A for example) by the other:

We compute the smallest number λ_0 such that $\lambda_0 B$ contains A and the greatest number μ_0 such that A contains $\mu_0 B$

and we define the Asplund's distance between A and B:

$$d_{As}(A,B) = Ln\left(\frac{\lambda_0}{\mu_0}\right)$$

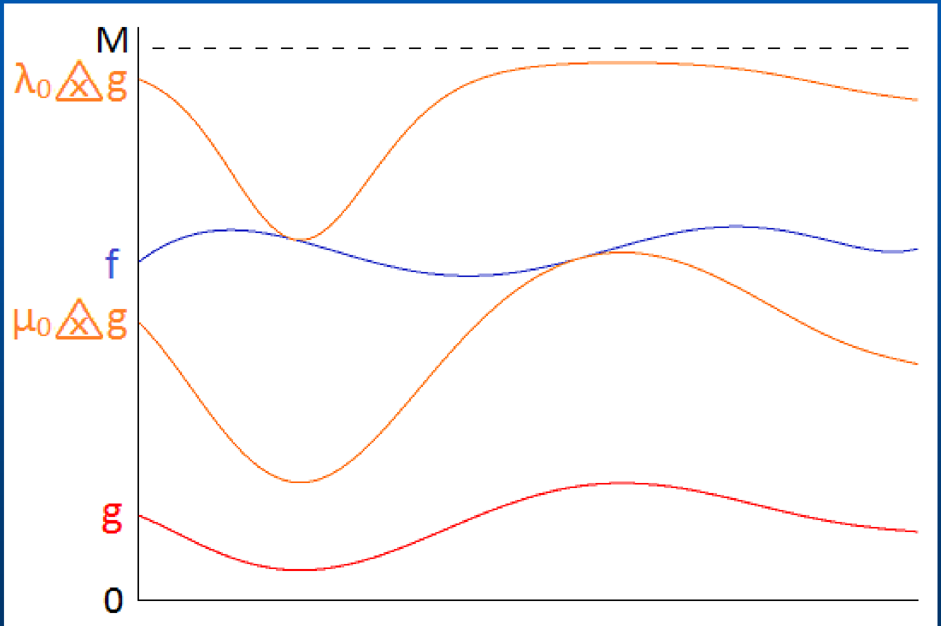


ASPLUND's Metrics

Multiplicative Asplund Metric

Now we propose to extend this approach to a pair (f, g) of images:

$$d_{As}^{\triangle\!\!\!\!\times}(f, g) = Ln\left(\frac{\lambda_0}{\mu_0}\right)$$

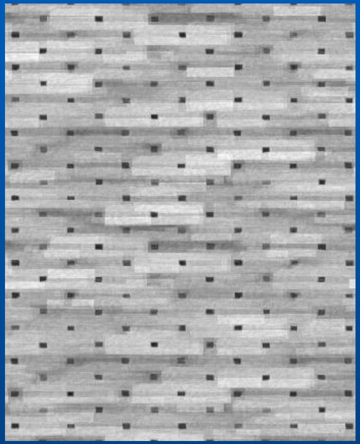
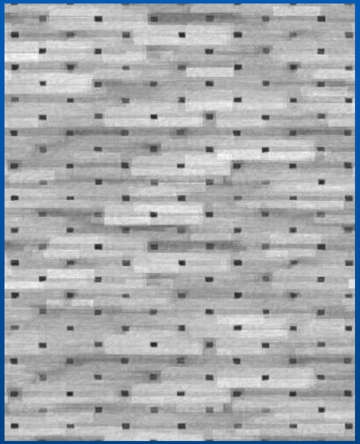


Note that such a distance does not change when one function is replaced by an homothetic $\Rightarrow d_{As}$ is insensitive to lighting variations modelized by $\lambda \triangle\!\!\!\!\times$.

Such a metric performs a "double sided probing" of f *by* g

ASPLUND's Metrics

Example of application : Target tracking

a)  b)  c)  d)  e) 

a) Initial image b) Bright target t_1 (a bright brick of the wall)

c) Corresponding Asplund's map (values of $d_{As}^{\triangle\!\!\!\!\times}(f|_{D_{t_1}}, t_1)$)

d) Dark target t_2 (a dark brick of the wall)

e) Corresponding Asplund's map (values of $d_{As}^{\triangle\!\!\!\!\times}(f|_{D_{t_2}}, t_2)$)

ASPLUND’s Metrics

Remark: The Multiplicative Asplund’s metric is *sensitive to noise*.

Such a drawback is shared with other “atomic” metrics like *Hausdorff*.

We have proposed a solution to limit this effect. It consists of discarding the most penalizing points (see the following Ref.)

M. Jourlin, E. Couka, B. Abdallah, J. Corvo and J. Breugnot, “Asplund's metric defined in the Logarithmic Image Processing (LIP) framework: A new way to perform double-sided image probing for non-linear grayscale pattern matching”, *Pattern Recognition*, 47 (9),(2014) 2908-2924.

ASPLUND's Metrics

More recently, I have introduced a new kind of Asplund's metric: the **Additive Asplund's Metric**. In fact, the approach is quite different: the double sided probing is no more performed thanks to homothetics of the probe, but by applying a LIP addition of a constant:

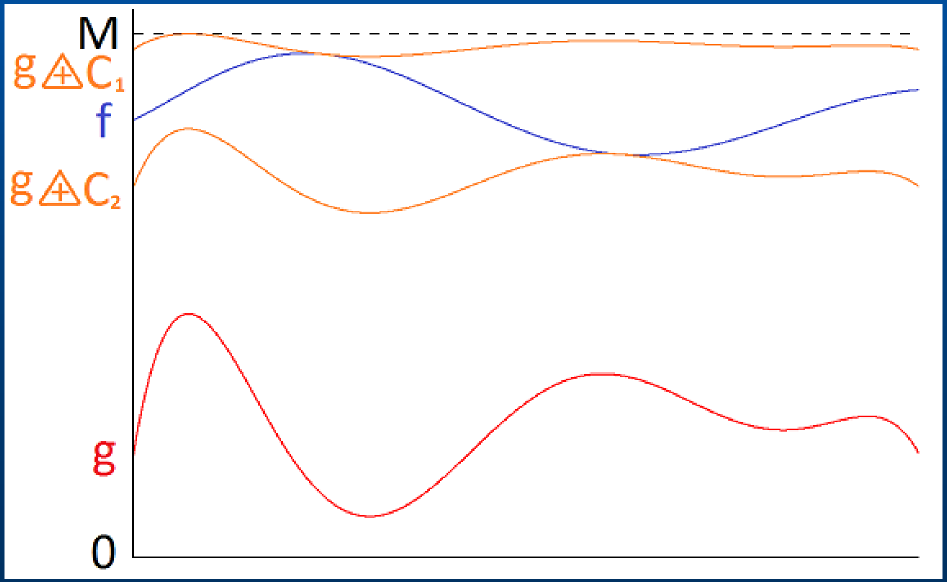
Given two grey level images f and g, we define two real numbers C_1 and C_2 according to:

$C_1 = \ Inf\{C, g \triangle\!\!\!+ C \geq f\}$

$C_2 = \ Sup\,\{C, g \triangle\!\!\!+ C \leq f\}$

where C lies $\in \,]-\infty, M[$

$d_{As}^{\triangle\!\!\!+}(f,g) = \ C_1 \triangle\!\!\!- C_2$
$\in [0, M[$



ASPLUND's Metrics

Advantage of this approach: We have seen the addition/ subtraction of a constant simulates exposure time variation, as well as variation of the source intensity.

⇨ the "additive" double sided probing becomes *insensitive to such variations*

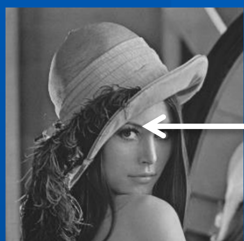
This opens the way to a lot of applications like pattern recognition, target tracking… independently of the lighting conditions

Recall: Thanks to the paper of Brailean, the consistency of the LIP operators with Human Vision permits to *process and analyze images acquired in reflexion as a human eye would do*.

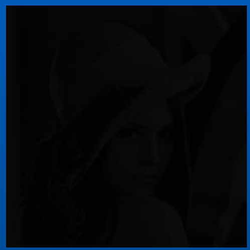
Let us begin by a theoretical example:

ASPLUND's Metrics

Consider Lena and a darkened image

f  

target (magnified)

$C \triangle\!\!\!\!\!\!+\, 240$ 

Compute the Asplund's maps of the target on f and f $\triangle\!\!\!\!\!\!+\, 240$:

ASPLUND’s Metrics

Real case:

Expo:

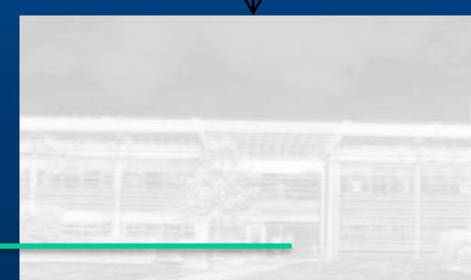
170ms

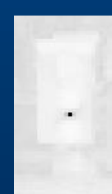
garbage can (magnified)

Expo:

50ms

Additive Asplund’s map





ASPLUND's Metrics

Our goal is not to expose in depth the possible use of Asplund's metrics.

Nevertheless, I must highlight the following point: When we compute the Asplund's distances $d_{As}^{\triangle\!\!\!\!\!\times}(f,g)$ and $d_{As}^{\triangle\!\!\!\!\!+}(f,g)$ we use in fact the equivalence classes $f^{\triangle\!\!\!\!\!\times}$ and $f^{\triangle\!\!\!\!\!+}$ of f. For example,

$$f^{\triangle\!\!\!\!\!+} = \{g, \exists K \in [0,255], f = g \mathbin{\triangle\!\!\!\!\!+} K \text{ or } g = f \mathbin{\triangle\!\!\!\!\!+} K\}$$

This explains that the result of $d_{As}^{\triangle\!\!\!\!\!+}\left(f^{\triangle\!\!\!\!\!+}, g^{\triangle\!\!\!\!\!+}\right)$ is insensitive to lighting variations simulated by the LIP addition of a constant.

ASPLUND's Metrics

Perspective: We have seen that *LIP operators are particularly efficient to enhance low-light images*. Nevertheless, such an enhancement obviously increase together the signal and the noise.On another hand, *Asplund's metrics are strongly insensitive to lighting variations and particularly to underlighting, but they remain sensitive to noise*. In such conditions, it appears that a step of noise filtering can improve the potential of Asplund's metrics. Some preliminary works show that *noise filtering obtained by means of "Deep Learning" approaches* performs well.

Thus we can expect to dispose of **powerful tools to perform images acquired under variable lighting**.

Image Processing under Variable Lighting: LIP Model and Asplund's Metrics

- References

[1] M. Jourlin, J.-C. Pinoli, (1988), "A model for Logarithmic Image Processing", *Journal of Microscopy*, Vol. 149, n°1, 21-35

[2] M. Jourlin, J.-C. Pinoli, (2001), "Logarithmic Image Processing: The mathematical and physical framework for the representation and processing of transmitted images", *Advances in Imaging and Electron Physics*, 115, 129-196

[3] M. Jourlin, Logarithmic Image Processing: Theory and Applications, vol. 195 of *Advances in Imaging and Electron Physics*, Elsevier Science, Academic Press,2016, 260p.

[4] J. Brailean, B. Sullivan, C. Chen, M. Giger, (1991), "Evaluating the em algorithm using a human visual fidelity criterion", *Int. Conf. on Acoustics. Speech and Signal Processing*, 2957–2960

[5] M. Jourlin, E. Couka, B. Abdallah, J. Corvo and J. Breugnot, "Asplund's metric defined in the Logarithmic Image Processing (LIP) framework: A new way to perform double-sided image probing for non-linear grayscale pattern matching", *Pattern Recognition*, 47 (9),(2014) 2908-2924.

[6] G. Noyel, M. Jourlin, "Asplünd's Metric defined in the Logarithmic Image Processing (LIP) Framework for Colour and Multivariate Images", IEEE International Congress on Image Processing, Québec, Septembre 2015

Image Processing under Variable Lighting: LIP Model and Asplund's Metrics

[7] V. Deshayes, P. Guilbert, M. Jourlin, "How simulating exposure time variations in the LIP Model. Application: moving objects acquisition", 14th International Congress for Stereology and Image Analysis Liège, July 7-10, 2015

[8] P. Guilbert, V. Deshayes, M. Jourlin, "Colour Contrasts and Associated Metrics Defined in the LIP Framework. Generated Neighbourhoods in the (x, y)-space", 14th International Congress for Stereology and Image Analysis Liège, July 7-10, 2015

[9] M. Carré, M. Jourlin, "Brightness spatial stabilization in the LIP framework", 14th International Congress for Stereology and Image Analysis Liège, July 7-10, 2015

[10] G. Noyel, M. Jourlin, "Double-sided probing by map of Asplund's distances using Logarithmic Image Processing in the framework of Mathematical Morphology", *13th International Symposium on Mathematical Morphology, ISMM*, *Springer International Publishing*, Fontainebleau, France, pp. 408-420, May 2017,

[11] G. Noyel, M. Jourlin, "A simple expression for the map of Asplund's distances with the multiplicative Logarithmic Image Processing (LIP) law," in *12th European Congr. for Stereology and Image Analysis*, Kaiserslautern, Germany, Sep. 2017