

# A perceptual image quality evaluation based on local spatial information

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## Abstract

This paper presents a new comparative objective method for image quality evaluation. This method relies on two keys points: a local objective evaluation and a perceptual gathering. The local evaluation concerns the dissimilarities between the degraded image and the reference image ; it is based on a gray-level local Hausdorff distance. This new Hausdorff distance uses a generalized distance transform which is studied here. The evaluation result is a local dissimilarity map (LDMap). In order to include perceptual information, a perceptual map based on the image properties is then proposed. The coefficients of this map are used to weight and to gather the LDM measures into a single quality measure. The perceptual map is tunable but it gives encouraging quality measures even with naive parameters.

*Keywords:* Image comparison, Hausdorff distance, distance transform, local dissimilarity measure, quality measure.

## 1 Introduction

Image quality evaluation is a key point in several domains including image compression algorithm assessment or graphical image quality evaluation. Even if the best method is the subjective method MOS (Mean opinion score), which is based on observers' evaluation, it is not always possible to seek it: it is subject to variations and it involves many people and a lot of time. An alternative is to use an automatic quality evaluation. In this frame, the measure can be estimated just on the transformed image itself or in comparison with a reference image. We focus on the latter kind of methods so-called comparative objective methods. There exists a lot of well known comparative objective methods like the Mean Square error (MSE) or the Peak Signal to Noise Ratio (PSNR), ... But none of the current methods take in account a perceptual evaluation because they are often based on a pixel to pixel difference and perceptual information include both local and global aspects of the image. In order to move closer to the evaluation of the final user, it is important to integrate a perceptual evaluation.

We propose a new method which is based on two key points: 1) a local objective evaluation and 2) a perceptual gathering. 1) Unlike to human vision, the pixel to pixel difference is very sensitive to small translations. A generalization of it to a less sensitive local measure has been developed for binary images in [1]: the so-called Local Dissimilarities Map (LDMap). It is based on the distance transform and several distance transform generalization to gray-level images are available. A comprehensive study of the LDMap generalization to gray-level images is presented here in quality measure aim. 2) Our method then exploits the spatial distribution of the dissimilarity measures gathered in the LDMap generalized to gray-level images thanks to a perceptual weighting that emphasizes image areas that are important for human vision. These weights, gathered in a so-called perceptual map, are based on brightness, shape and texture; they can be tuned in function of the final application. Our method results in a single measure. The proposed measure has been compared to subjective evaluations on the test image base *IVC database* and gives encouraging results. The two key points are detailed in the following sections.

## 2 The Local Dissimilarity Map

### 2.1 Definition

The LDMap is based on a local and adaptative evaluation of dissimilarities between images. It has been first defined on binary images via a local measure of dissimilarities, and is based on a distance between a pixel and a set of pixel. When Hausssdorf distance is used for the local measure, the formula of the LDMap is simple (see Definition 1) and allows to generalize easily the LDMap to gray-level images. Fig.1 illustrates the LDMAP between the image of letters *CO* and the image of letters *ET*.

**Definition 1** *LDMap*

Let  $I_1, I_2$  be two images,  $x \in \mathbb{R}^2$  a pixel, the LDmap between  $I_1$  and  $I_2$  is defined from  $\mathbb{R}^2$  to  $\mathbb{R}$  by

$$LDMap(x) = \frac{|I_2(x) - I_1(x)|}{\max(|I_2(x) - I_1(x)|)} \max(d(x, I_1), d(x, I_2)) \quad (1)$$

where  $d$  is a distance transform (DT), measuring the distance between a point and a set of points.

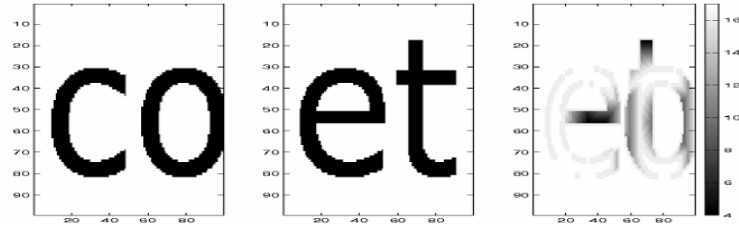


Figure 1: Letters CO and ET and their LDMAP containing theirs local dissimilarities

This formula (1), with a distance transform, allows to generalize the LDMap to gray-level images. The distance transforms are indeed generalized to gray-level images and higher dimension images.

The aim of the distance transform is to calculate the minimum distance between each pixel of the form  $F$  to the background  $Bg$  of the image as illustrated in Fig.2. For binary pictures, distance transform takes in count a 2D distance as the Euclidean distance, Mahalanobis distance, ...

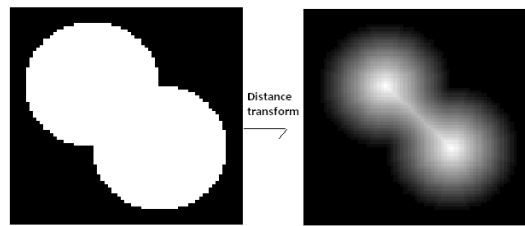


Figure 2: Distance transform of the binary image composed with a white pixel form and a black pixel background

### 2.2 The distance transform and its continuous generalizations

The DT are based on an underlying distance between pixels. The different DT come from distinct underlying distances. We focus here on the underlying distance computation so as to choose the most adapted DT to image processing.

For binary images, pixels can be seen as points of the plan. The distance transforms are then based on 2D mathematical spatial distances (e.g. the Euclidean distance, the Mahalanobis distance and so on).

For gray-level images, the gray-level dimension is added to the two plan dimensions. There are different ways of including this dimension in the distance computation, and they influence the produced dissimilarity measure. Considering a gray-level image as a set of points of  $\mathbb{R}^3$ , the image is a surface in  $\mathbb{R}^3$ . Then the distance between two points of this surface is the shortest path between these two points accorded to a path-length measure. There are two possibilities in the literature for this measure: the measure of the length of the path on the image surface or the measure of the area of the surface under the path on the image surface. A formal definition is given thereafter (Definition 2).

**Definition 2** *Let  $I$  be a continuous function defined on  $X$  the image support :*

$$I : \begin{cases} X \longrightarrow \mathbb{R} \\ (x, y) \mapsto I(x, y) \end{cases}$$

and let  $\pi : t \in [0, 1] \mapsto \pi(t) \in \mathbb{R}^2$  be a continuous path between the pixels  $p$  and  $q$  of  $I$ . The length of the path  $\pi$  (so-called  $L_\pi$ ) is given by

1. the length of the path on the image surface

$$L_\pi^1 = \int_0^1 |I'(\pi(t))| dt \quad (2)$$

2. the area of the surface under the path on the image surface

$$L_\pi^2 = \int_0^1 |I(\pi(t))\pi'(t)| dt \quad (3)$$

Both of these possibilities have been implemented in the discrete space. The discretization step implies also choices so the different versions of the DT underlying distances are briefly introduced in the next section.

### 2.3 Discrete implementations of the distance transforms

The presentation of the different DT is too long to be detailed here so we will only give a brief insight on them.

1. first type methods (introduced by P. Toivanen):

- the Distance Transform On Curved Space [5, 6] (DTOCS), the Weighted DTOCS (WDTOCS)
- the method improvements: 3-4-DTOCS and Optimal WDTOCS (Opt-WDTOCS).

2. second type methods

- the Gray-Weighted Medial Axis Transform [2] (GRAYMAT) introduced by G. Levi and U. Montanari. Its underlying distance is based on the pixel difference value and as a consequence, it promotes low gray-level pixel paths. It is aimed at skeletization.
- the Gray-Weighted Distance Transform [4] (GWDT) introduced by D. Rutovitz

### 2.4 Comments and choice

It is quite difficult to anticipate the qualities of the different DT from their definition, nevertheless, we have chosen the second family method because their underlying distance is closer to the notion of distance in the graylevel dimension. The second family indeed, takes into account differences of gray levels on a path and the spatial distance. It seems to us more appropriate than the first family which overwrites some spatial information for the benefit of gray level information (see Fig. 3). In the second family the differences between the versions are minor. Nevertheless the 3-4-DTOCS seems the most interesting to us because it does not underestimate the diagonal distance unlike to DTOCS. Our study on this point should be furthered to detail the choice.

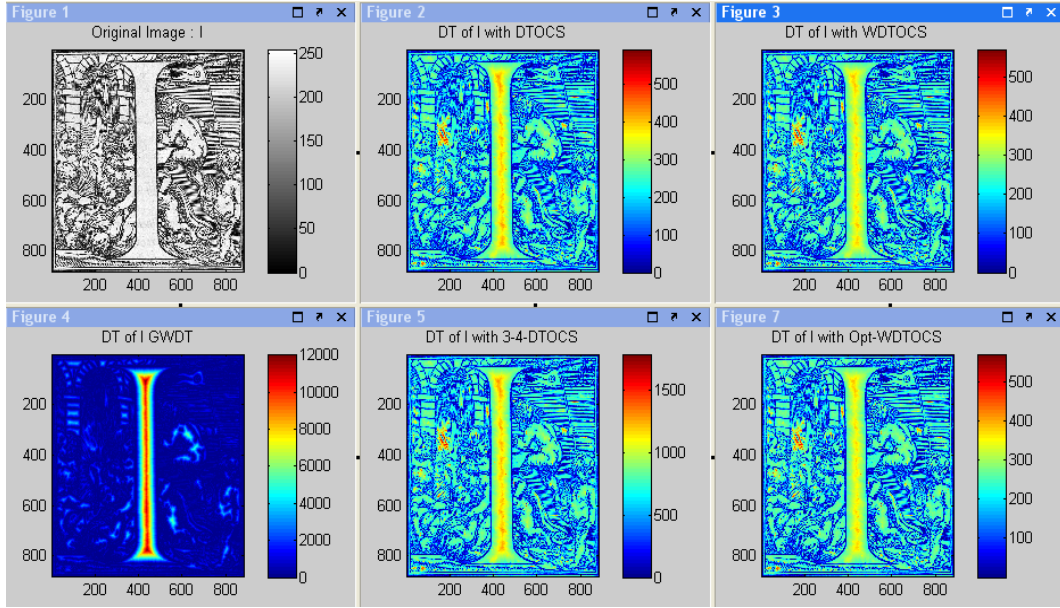


Figure 3: An example of some DT

### 3 The quality measure

We want to take advantage of the spatial information contained in the LDMap to include perceptual information. The dissimilarities between two images are already quantified in the LDMap. Given an original image (reference image, original image) and a transformed image (compressed image, degraded image ...), then the sum of the coefficients in the LDMap (computed between these two images) can represent the transformation evaluation between the compared images. Nevertheless, it is known that the visual perception does not take the entire image into account [3]. So we construct a perceptual map (PMap) in order to use the local information of the LDMap and the observer's attention model, and we associate the two maps to obtain a single measure. The PMap combines the brightness, shape, texture attributes which are factors the eye is sensitive to. Each attribute is calculated on the reference image and for each one we define a map: for the brightness  $B$ , for the shape  $S$  and for the texture  $T$ . The Pmap is defined as weighted sum (Definition 3) of  $B$ ,  $S$  and  $T$ . Then the PMap is normalized in order to be a weighting Map. Figure 4 presents an example of PMap.

**Definition 3** *PMap*

Let  $A$  be an image, the PMap of  $A$  is defined by :

$$PMap_A = p_1 \cdot B + p_2 \cdot S + p_3 \cdot T \quad (4)$$

Where  $p_1, p_2$  and  $p_3$  are the weights respectively of the brightness, the shape and the texture, and where  $B$ ,  $S$  and  $T$  are normalized.

By balancing the LDMap with the PMap as illustrated Fig. 5, we obtain the perceptual local dissimilarity map (PLDMap), containing local information on dissimilarities and visual perception, we can measure the quality of the transformed image by extracting the maximum value or the mean value of the PLDMap. We have study the two values and the maximum appears to be the best quality measure.

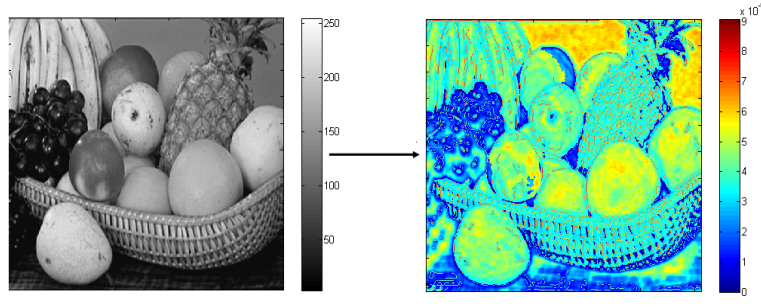


Figure 4: PMap with  $p_1=2$ ,  $p_2=1$  and  $p_3=-2$

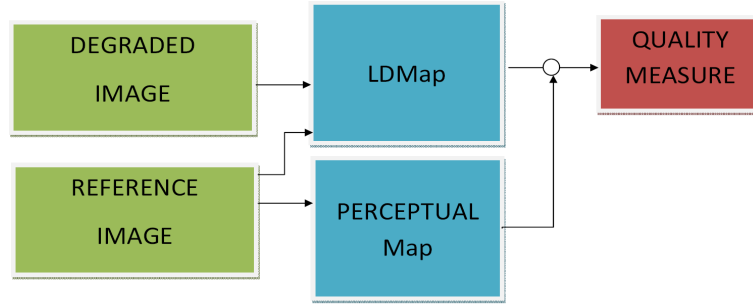


Figure 5: Scheme of the quality measure method

## 4 Results, conclusion and future works

The proposed measure has been compared to subjective evaluations on a test image base and gives encouraging results. The Fig.6 shows our first results for one image compressed with different rates of compression. The smaller our measure, the better the quality, conversely for the Mean Opinion Score (MOS) the higher the score, the better the quality. Test results on a bigger database and in comparison with other quality are coming soon. In the future, the LDMap could be developed to color images and the PMap could take in account other attributes. We can refine weights of maps constituting the PMAP.

|                 | clown_r1.bmp | clown_r2.bmp | clown_r3.bmp | clown_r4.bmp | clown_r5.bmp |
|-----------------|--------------|--------------|--------------|--------------|--------------|
| <b>Max CDLP</b> | 0,009692926  | 0,016729111  | 0,0198354    | 0,026313345  | 0,018254167  |
| <b>MOS</b>      | 4,423076923  | 3,769230769  | 2,384615385  | 1,807692308  | 1,115384615  |

|                 | fruit_r1.bmp | fruit_r2.bmp | fruit_r3.bmp | fruit_r4.bmp | fruit_r5.bmp |
|-----------------|--------------|--------------|--------------|--------------|--------------|
| <b>Max CDLP</b> | 0,013782443  | 0,011248402  | 0,02158169   | 0,019044261  | 0,021478231  |
| <b>MOS</b>      | 4,423076923  | 4            | 2,961538462  | 1,769230769  | 1,423076923  |

Figure 6: First result on two images compressed with different rates ( $r_1 < r_2 < r_3 < r_4 < r_5$ ) and with  $p_1=4, p_2=1, p_3=-2$

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