A Local Color Correlation Measure for Color Image Comparison

A. Tremeau, V. Pugnet, E. Dinet and B. Laget
Equipe Ingénierie de la Vision, Laboratoire TSI
GIAT Industries, Saint Etienne, France

Abstract

In this article we propose to use a local color correlation measure for color image comparison. The interest of this measure is that it takes into account basic characteristics linked to the human visual perception. Consequently it enables us to subjectively evaluate color image processing methods as for image quality.

Introduction

In image analysis we are faced to numerous problems more or less difficult to solve. The image comparison is one of the most interesting problems to solve because it involves two fields of study. The first one relates to image analysis in accordance with human visual perception inorder to reach results that correspond to the human visual judgement. The second field of study deals with image processing techniques such as segmentation, quantization or compression. As far as an objective image comparison is concerned, we can first of all evaluate the result of the process itself with respect to image quality, we can likewise compare the results of two processes working on the same image with respect to achieved images. This will enable us to understand or to evaluate the reasons why a particular process is not optimal as for image quality and to improve it therefore.[1]

Although image comparison processes have largely evolved during the last few years, they do not enough take into account visual parameters to be considered being relevant with reference to visual judgement.[2] Even if the experience and theory show that it is extremely difficult to define an objective process that involves the most significant phenomena of the visual judgement, it has been shown that we can nevertheless define an heuristic process from some basic characteristics linked to human visual perception.[3,4]

In this article we propose to use a color correlation measure in order to define a subjective method for color image quality evaluation.[5] Moreover, rather than defining a global measure of image differences such as the sum of squared differences, we propose first to compute this color correlation measure for each pixel taking into account its neighborhoods, secondly to display all these measures like a comparison image and thirdly to define a global measure according to the spatial distribution and to the amplitude of these local measures.[6] As far as such a process is concerned, we can show that our measure is relevant in terms of human visual judgement. Furthermore we can put stress on image areas for which the correlation measure is the most important, that is we can focus the attention of the observer on elements for which image differences are more perceptible.

Brightness Difference

Three criterions have been used to define the color correlation measure. The first one involves the local brightness difference which is defined as follows :

$$B(x, y) = 1 - \frac{\left|\text{Log}[\mu^I(x, y)] - \text{Log}[\mu^J(x, y)]\right|}{\text{LogL}_{max} - \text{LogL}_{min}} \tag{1}$$

where :

* L_{max} and L_{min} are the lowest and the highest grey levels respectively of the image under study,
* $\mu(x,y)$ is the average value of the grey levels of a neighborhood m*m centered at the pixel (x,y) and defined as follows :

$$\mu^I(x, y) = \sum_{i=-m}^{m} \sum_{j=-m}^{m} \omega(i, j) f^I(x + i, y + j) \tag{2}$$

where :

* $f^I(x, y)$ represents the grey level of the pixel (x,y) of the image I,
* ω is a weighting function which is unimodal (in order to put emphasize on the central pixel), symmetric and normalized. It may be a Gaussian function.

This criterion only involves the brightness difference without taking into account the chromatic difference because visual experiments have shown that the brightness sensitivity prevails over the chromatic sensitivity. Moreover no order relation exists between colors : we can not define therefore an average value for a set of colors except if these colors are almost similar.

Correlation Measure

The second criterion which is used to define the color correlation measure involves at the same time the local emergence difference and the local dispersion difference.[7,8] It is defined as follows :

$$C(x,y) = \frac{\sum_k \mathrm{cov}_k(x,y)}{\sqrt{\sum_k (\sigma_k^I(x,y))^2}\sqrt{\sum_k (\sigma_k^J(x,y))^2}} \qquad (3)$$

where :
* k=1, 2, 3 represents the k-axis of the color space used to describe a color (RGB or L*a*b* in our study)
*

$$\mathrm{cov}_k(x,y) = \sum_{i=-m}^{m}\sum_{j=-m}^{m} \omega(i,j) f_k^I(x+i,y+j).f_k^J(x+i,y+j)$$
$$-\mu_k^I(x,y).\mu_k^J(x,y) \qquad (4)$$

represents the covariance for the pixel (x,y) between the two images I and J according to the k-axis and to the specified neighborhood,
where :
* $f_k^I(x,y)$ represents the value of the pixel (x,y) on the k-axis for the image I,
* $\mu_k^I(x,y)$ is the average value of the k-component values of the neighborhood m*m centered at the pixel (x,y),
*

$$(\sigma_k^I(x,y))^2 = \sum_{i=-m}^{m}\sum_{j=-m}^{m} \omega(i,j)(f_k^I(x+i,y+j))^2 - (\mu_k^I(x,y))^2 \qquad (5)$$

represents the variance around the average value according to the k-axis and to the neighborhood m*m under study for the image I.

When *one* of the variance of the two images under comparison is null or equal to ε (not far from zero), the criterion C(x,y) is not defined. We have then designed a third criterion V(x,y) as follows :

$$V_k^I(x,y)^2 = \frac{\sigma_k^I(x,y)^2}{\underset{M}{\mathrm{Max}}(\mathrm{sigma}_k^I(i,j)^2)} \qquad (6)$$

where :
* $\sigma_K^I(x,y) \neq 0$,
* M represents the neighborhood m*m centered on the pixel (x,y).

$V_k^I(x,y)^2$ represents a mono-dimensional component. The tri-dimensional criterion V(x,y) is a 3*1D combination of the three $V_k(x,y)$ (with the norm L_2 for instance) or is based on a vector analysis (using the Max function according to a vector definition instead of a scalar definition) that is a 3*D analysis.

The criterion we have used to compute the images shown in the Figures is :

$$V(x,y) = \sqrt{\sum_k \frac{\sigma_k^I(x,y)^2}{\underset{M}{\mathrm{Max}}(\mathrm{sigma}_k^I(i,j)^2)}} \qquad (7)$$

where :

$$\mathrm{sigma}_k^I(i,j)^2 = \omega(i,j) f_k^I(x+i,y+j)^2 - \mu_k^I(x,y)^2 \qquad (8)$$

Color Correlation Measure

The color correlation measure that we propose is then defined as follows:

$$D(x,y)=C(x,y).V(x,y).B(x,y) \qquad (9)$$

The different values of D(x,y) with respect to the values of $\sigma^I(x,y)$ and $\sigma^J(x,y)$, the *color variances* of image I and image J respectively, are below defined :

* if $\sigma^I(x,y) \neq 0$ *and* $\sigma^J(x,y) \neq 0$
V(x,y)=1
D(x,y)=C(x,y).B(x,y)

* if $\sigma^I(x,y)=0$ *or* $\sigma^J(x,y)=0$
C(x,y)=1
D(x,y)=V(x,y).B(x,y)

* if $\sigma^I(x,y) = \sigma^J(x,y) = 0$
V(x,y)=C(x,y)=1
D(x,y)=B(x,y)

These three criterions have been calibrated in order to have D(x,y) in the range [0,1] : 0 corresponds to a *no-correlation* event, and 1 corresponds to a *total-correlation* event.

The definition of V(x,y) and C(x,y) allows the continuity of the function D(x,y) with respect to a small variation of σ around zero. We may also only use the general definition of the function C(x,y) by adding a same noise to the two images in order to avoid having any value of σ equal to zero. The added noise should be gaussian with a sigma as small as possible. This noise will then also appear in the comparison result. It could be deleted by filtering the comparison image with a filter based on the structure of the added noise and the neighborhood on used to compute D(x,y).

This measure has been used to evaluate the result of different color image processing techniques such as color segmentation or color quantization. The image comparison method is obviously the same for each process. Thus we obtain from both the original image (I) and its processing result (J) a new image of local differences (D) for which each pixel value has been computed according to the equation (9). This new image has to be rescaled in order to be displayed on a screen. The use of false color look-up-table allows the most noticeable differences to be well displayed.

Discussion and Results

Two examples of *comparison image* are shown in Figure 2b and 3b. Two segmentation processes, namely process 1 and process 2, were applied to the same image *Peppers* shown in Figure 1. The achieved segmented images are shown in Figure 2a and 3a. We can note that the study of segmented image for the comparison process implies computation of D(x,y) with one σ equal to zero as far as each segmented region presents the average color of all the pixels of this region on the original image.

The comparison images presented in this article have been computed with the tri-dimensional color variance and covariance resulted from the mono-dimensional variance and covariance vectors respectively and are defined as follows:

$$\sigma^{I}(x,y) = \sqrt{\sum_{k} \sigma_{k}^{I}(x,y)^{2}} \tag{10}$$

$$\mathrm{cov}(x,y) = \sum_{k} \mathrm{cov}_{k}(x,y) \tag{11}$$

We also have directly applied different norms as L_1, L_2, and L_∞ to the color vector : *a* color value has been computed for each pixel with respect to the chosen norm, and then the average, variance and covariance values used for D(x,y) computation have been calculated with this color value. The norms L_1 and L_2 do not provide any interesting results: the weakness of the segmentation for example are not clearly revealed. The norm L_∞ gives similar result to the vector computation above defined.

The results of the comparison process are shown in Figure 2b and 3b. False color look-up table is used in order to emphasize the different types of correlation we may obtain: the green pixels correspond to well-segmented one, the red pixels represent segmentation error, and the white pixels are *no-decision* one (the influence of these pixels is linked with the type of the application of the segmentation process). The used neighborhood is a 3*3 one.

We can then define two *quality index.* The first one is named the *visual quality index (VQI)***.** It corresponds to the comparison image which emphasizes the *error-processed* areas and the *well-processed* areas due to the process under study. For instance, on the one hand it clearly appears that the segmentation process 1 better works than the process 2 as far as object segmentation or pattern recognition is concerned (more homogeneous regions are present in Figure 2c than in Figure 3c). On the other hand, better results are achieved with the segmentation process 2 than with the process 1 as far as details, luminance difference, small color difference discriminations are concerned. Moreover, these comparison images clearly point out the weakness of a segmentation process. The process 1 does not segment for example two objects that present similar colors (green pepper and yellow one on the right up side of figure 1).

Furthermore, thanks to the comparison image we can immediatly locate the most perceptible differences with regard to the sensitivity of human observer : for instance a small difference in an homogeneous area focuses the attention of the observer whereas the same small difference in a texturized area does not obviously appear to the observer.

We can then define an *average global visual index* in terms of spatio-color distribution instead of mean square error. This index will allow the user to differentiate the local distortions from distortions appearing in area which presents numerous and closely related distortions. The pyramidal method is well designed to compute this *average global visual index.*

These informations may help the designer or/and the computer itself to improve the segmentation process or any process under study.

We have used the 3*3, 5*5 and 7*7 neighborhoods. The first one provides much more accurate information concerning details, edges than the two others. The 7*7 mask allows a *filtering* of the result, that means only large differences are displayed. This is a well pre-visualisation of the results that the user can expect.

The second index is a *quantitative quality index (QQI)*. It is based on the ratio of high level pixels to low level pixels. It is computed on a filtered comparison image in order to avoid taking into account noisy pixels due to noise of the images under study or due to computation noise. This index immediatly gives the performance level in terms of visual quality of the process we are looking for, relatively to a reference process. That means this quantitative quality index corresponds to a *relative measure*: two processes then can be easily compared. For instance, the QQI of process 1 is equal to 6.2 while the QQI of process 2 is 7.5 (with the 3*3 neighborhood). That is, process 2 provides better result than process 1 in terms of human sensitivity.

We can note that these two index measure not only the segmentation process performance in terms of regions versus edges, but also the difference between the color of each segmented area and the colors of its original area. The way to compute the colors of the segments has to be taken into account to compute D(x,y), and especially V(x,y).

Perspective

We are defining a *reference image base* in order to calibrate the quantitative quality index.[9] Each reference image shall contain one or several well-known information as form, details, luminance differences, texture, color differences…Each process under consideration will be tested with this image base. Then two kinds of information will be available, corresponding to the two quality index above defined. The first one will point out the performances and the weakness of the process itself. We will be then able to evaluate whether such a process is well designed for such an application. The second one deals with comparison of different processes. Applying the image base to the different processes, we will be able to evaluate the best process with respect to a particular application.

Both the quantitative and the visual quality index may help not only the user but also the designer/computer to choose and/or improve a segmentation, quantization or compression process with regard to the information of the images to process.

Figure 1. Original image Peppers RGB

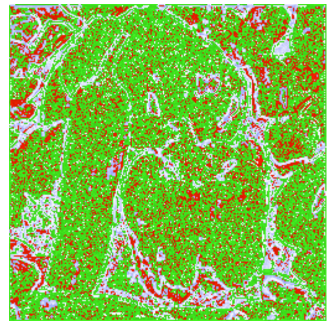

Figure 3a. Segmented image - Process 2

Figure 2a. Segmented Image - Process 1

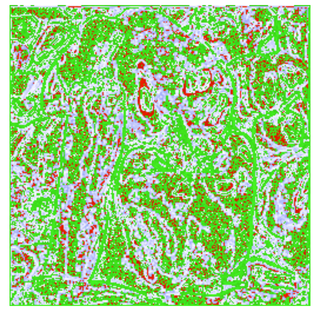

*Figure 3b. Comparison image.3*3 neighbohrood.*

*Figure 2b. Comparison image. 3*3 neighborhood*

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