Quality of color image filtering processes

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Abstract

The aim of this study is to demonstrate that the perceived quality of a filtered image reflects its degree of correspondence to both the original image and to the memorized reality. Differents descriptors are given to prove that there is effectively a relationship between these perceived attributes. To illustrate our purpose we have used differents color filtering operators, including some original ones in terms of color image processing.

1. Introduction

The aim of this paper is to define some objective quality descriptors, for color filtered images, which reflect closely the quality attributes perceived by observers. Image filtering is commonly used in image processing to reduce noise, to enhance contrast, to strengthen image dynamic range, to reduce the color gamut of an image, and so on. Indeed, the choose of a filtering operator depends first of all of images data and of fields of processing considered, next of the quality of the resulting image.

It is interesting to note that multivariate statistical filtering is an "old" signal processing topic which have led to widely known and useful filters. Let us note nevertheless that most of these filters can not be extended to color images because most of color features are dependant, so they can not be analyzed separately. Moreover, most of these filters compare pixel values according to rules which can not be used in color, because there is no order relation between colors. Consequently, there is not a lot of filters which can be used to process adequately color images. It is therefore absolutely necessary to justify the relevance of a color filter before using it. That can be done either from a theoretical and analytical point of view, either from an experimental and comparative study. Most of study insists on theoretical aspects without enough taking into account the perceived quality of resulting color images. Inversely, in this study, we make the hypothesis that perceived quality of filtered images is essential for observers ; that will enable us to understand why some color filters can not be efficient. Indeed, we want to prove that there is a relationship between the perceived quality of a color filtering process and its usefulness in terms of image processing.

2. Color filtering operators

In this study, we have considered several color filter operators, some are widely known but useless for color images processing, other most recent are less known but more relevant, especially for mixing color values. These filters can be defined succinctly according to keywords attributes, such as :

- *a gaussian operator*, which is applied separately on each color feature, then which combined each filtered image to others according to an additive rule. The problem comes from that color features are dependant.
- *a morphological operator*, which is applied separately on each color feature, then which combined each filtered image to others according to an additive rule. The problem comes from that color features are dependant, and that there is no order relation between colors.
- *a median color operator*, which is applied on the most relevant color feature according to an order relation relative to the 3-dimensional transform used to obtain a 1-dimensional signal.[1] The problem comes from that these order relations reflect closely the order relation given by the main color feature of the image considered (which corresponds closely to the luminance feature). To overcome this problem, it is necessary to define a local trans-

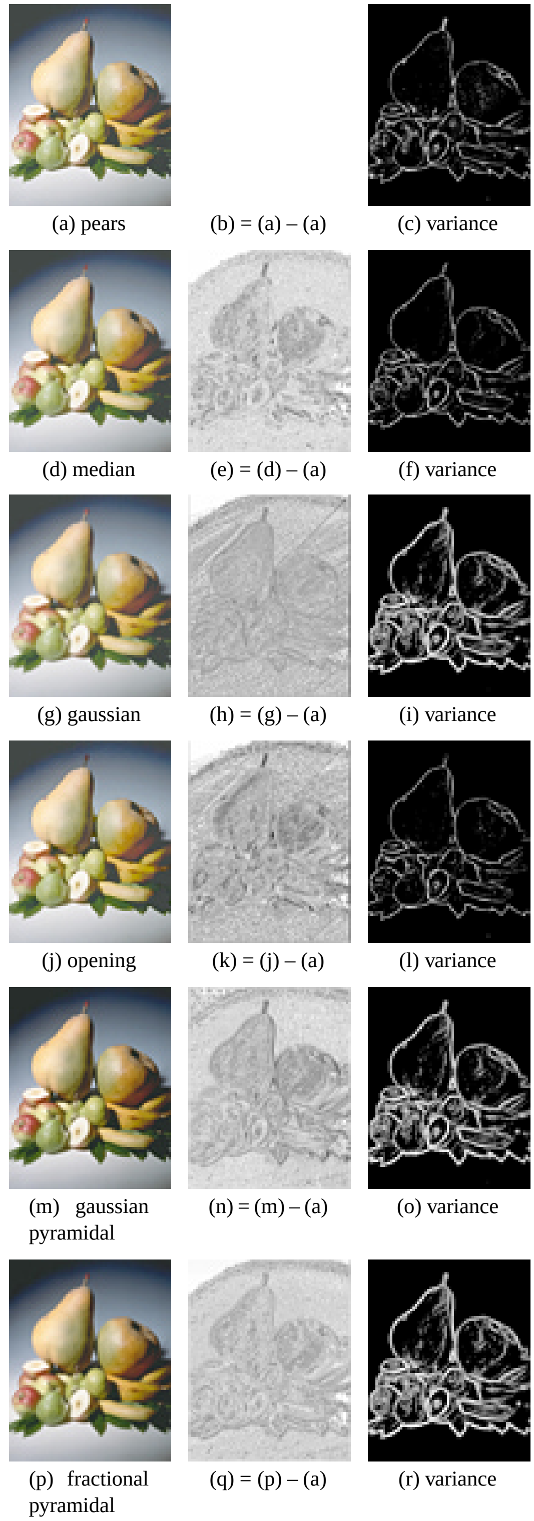
[1] As example, two order relations have been proposed in [1], one is linked to a bit mixing process, the other is linked to a principal component analysis process.

form and a local order relation, but this operation is time consuming [1].

- *a gaussian pyramidal color operator*,[2] which is applied separately on each color feature, which combined each filtered image to others according to an additive rule, then which is resized to the same dimension as the original image. The problem comes from the size of the kernell which may create a blockiness effect, and from the number of levels, that we can compute, which are quite low.
- *a fractional pyramidal color operator*.[3] The principle is the same as for the gaussian pyramidal color operator, nevertheless we have the possibility to choose the resolution level among an "infinity" of solutions, in order to modulate the filtering operator, in varying the overlapping rate between neighboring pixels [3]. The problem comes from the analytical definition of this tool which has not been generalized to all cases of study.

3. Proposed descriptors

In previous work [5], we have shown that perceived quality of color images depends not only of a global attribute but rather of the conjunction of local attributes, which depend themself both of the images studied and of the applications considered. We have thus shown that the perceived quality of a processing image depends of its degree of local correspondence to the original image. In the continuation of this hypothesis, we make an another hypothesis according with the perceived quality of a filtered image reflects both its degree of correspondence to the original image and its degree of correspondence to the memorized reality. That is to say, images differences must be the less noticeable as possible and the visual aspect of the filtered image must be the most "natural" as possible. In order to analyze the quality of filtered images, we propose to use four local descriptors of images differences and two image quality descriptors. Moreover, we suggest to compute these descriptors according to the $L^*a^*b^*$ color space because it is one of the most uniform color spaces to discriminate colors and to compute color distances. Our aim is to demonstrate that these descriptors reflect closely the degree of perceived quality of filtered images.



(a) pears (b) = (a) – (a) (c) variance

(d) median (e) = (d) – (a) (f) variance

(g) gaussian (h) = (g) – (a) (i) variance

(j) opening (k) = (j) – (a) (l) variance

(m) gaussian pyramidal (n) = (m) – (a) (o) variance

(p) fractional pyramidal (q) = (p) – (a) (r) variance

Figure 1: 1) Examples of color Images resulting of filtering processes of size 5×5. 2) Images of local differences between each of these images and image of figure 1(a). 3) Image of local variance values computed with a 5×5 neighborhood mask. (N.B. Pyramidal images are computed with the same kernel width and are displayed with the same resolution as the original image.)

[2] The images given in this article are computed for the level 1 of the pyramid.

[3] The images given in this article are computed from the level 3 of the pyramid with a rate of 5/4.

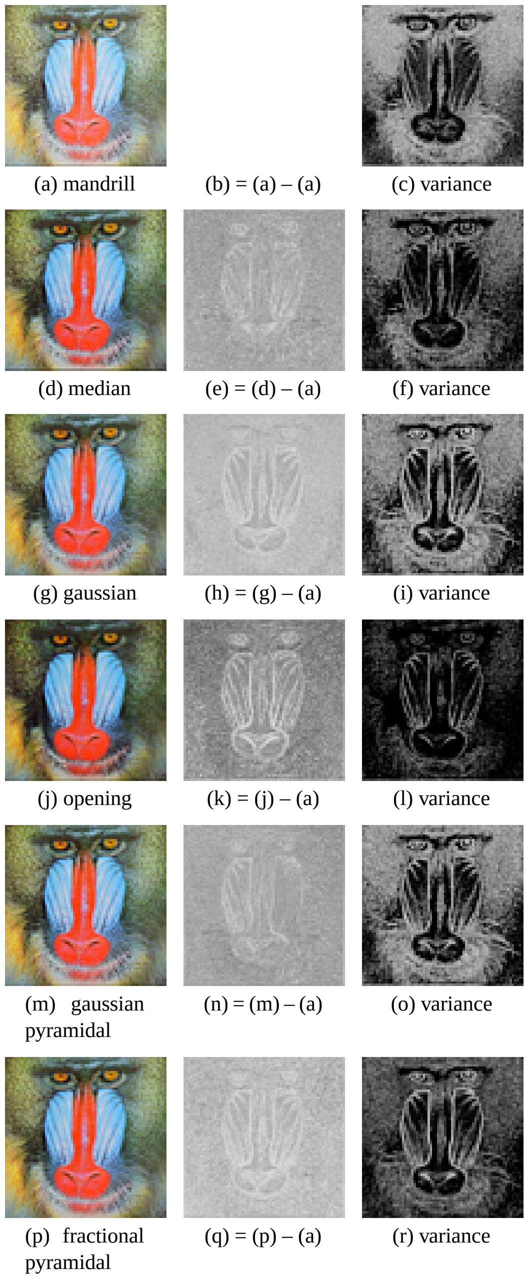


Figure 2: 1) Examples of color Images resulting of filtering processes of size 5×5*. 2) Images of local differences between each of these images and image of figure 2(a). 3) Image of local variance values computed with a* 5×5 *neighborhood mask. (N.B. Pyramidal images are computed with the same kernel width and are displayed with the same resolution as the original image.)*

3.1. Local images differences descriptors

The four descriptors used in this study are computed, pixel by pixel, according to a gaussian mask ($\omega(i,j)$) of size 5×5, by difference to the reference image. Let be I the original image and J the filtered image to be compared to I. These descriptors have been introduced in [5] to measure :

- the local brightness difference

$$D_b(x,y) = 1 - \frac{|\log\ \mu_L^I(x,y) - \log\ \mu_L^J(x,y)|}{\log L_{\max}(x,y) - \log L_{\min}(x,y)}$$

- the local color difference

$$D_c(x,y) = 1 - \frac{\sqrt{(\mu_a^I(x,y) - \mu_a^J(x,y))^2 + (\mu_b^I(x,y) - \mu_b^J(x,y))^2}}{\sqrt{(a_{\max}(x,y) - a_{\min}(x,y))^2 + (b_{\max}(x,y) - b_{\min}(x,y))^2}}$$

- the local dispersion cross-difference

$$D_d(x,y) = 1 - \max \left[\left(\frac{|e^{II}(x,y) - e^{IJ}(x,y)|}{\max_{l=I,J} e^{Il}(x,y) - \min_{l=I,J} e^{Il}(x,y)} \right), \left(\frac{|e^{JJ}(x,y) - e^{JI}(x,y)|}{\max_{l=I,J} e^{Jl}(x,y) - \min_{l=I,J} e^{Jl}(x,y)} \right) \right]$$

- the local correlation measure

$$D_{cm}(x,y) = \frac{\sum_{c=L^*,a^*,b^*} cov_c^{IJ}(x,y)}{\sqrt{\sum_{c=L^*,a^*,b^*} \sigma_c^I(x,y)^2} \times \sqrt{\sum_{c=L^*,a^*,b^*} \sigma_c^J(x,y)^2}}$$

These formula require to compute :

– $\mu_c^l(x,y)$ the mean c-value ($c = L^*, a^*$ or b^*) (l = I or J) of neighborhood $V(x,y)$, given by :

$$\frac{1}{Card\ V(x,y)} \sum_{(x',y') \in V(x,y)} \omega(x',y') \,.\, c^l(x',y')$$

– $c_{\max}(x,y)$ the maximal c-value of neighborhood $V(x,y)$, given by :[4]

$$\max_{(x',y') \in V(x,y)} (c^I(x',y'), c^J(x',y'))$$

[4]Likewise for the minimal c-value $c_{\min}$.

– $\sigma_c^l(x,y)$ the variance and $cov_c^{IJ}(x,y)$ the covariance c-values, of neighborhood $V(x,y)$, of images I and J, given by :

$$\frac{1}{Card\,V(x,y)} \sum_{(x',y')\in V(x,y)} \omega(x',y'). \left(c^l(x',y') - \mu_c^l(x,y)\right)^2$$

$$\frac{1}{Card\,V(x,y)} \sum_{(x',y')\in V(x,y)} \omega(x',y'). \left(c^I(x',y') - \mu_c^I(x,y)\right)\left(c^J(x',y') - \mu_c^J(x,y)\right)$$

– $e^{ll}(x,y)^2$ the emergence of each pixel $(x,y) \in l$, relatively to its neighborhood $V(x,y) \in l$, given by :

$$\frac{1}{Card\,V(x,y)} \sum_{(x',y')\in V(x,y)} \omega(x',y'). \sum_{c=L^*,a^*,b^*} \left(c^l(x,y) - c^l(x',y')\right)^2$$

– $e^{IJ}(x,y)^2$ the cross-emergence of each pixel $(x,y) \in I$, relatively to the neighborhood $V(x,y) \in J$, given by :

$$\frac{1}{Card\,V(x,y)} \sum_{(x',y')\in V(x,y)} \omega(x',y'). \sum_{c=L^*,a^*,b^*} \left(c^I(x,y) - c^J(x',y')\right)^2$$

– $\max_{l=I,J} e^{Il}(x,y)$ the extremal emergence values, which are given by :

$$\max_{(x',y')\in V(x,y)} \left(e^{II}(x',y'), e^{IJ}(x',y')\right)$$

These four descriptors have been defined according to the same scale ranking from 0 to 1. Value 0 (displayed in black) corresponds to most noticeable differences and 1 corresponds to none noticeable differences (displayed in white). They have been combined together as follows to define an objective measure of color image differences.

$$D(x,y)^2 = \frac{1}{4}\left(D_b(x,y)^2 + D_c(x,y)^2 + D_{dc}(x,y)^2 + D_{cm}(x,y)^2\right)$$

Images resulting of the combination of these local descriptors are given in figures 1 and 2. It is interesting to note that effectively the more a filtering process introduces deteriorations on an image, the more these deteriorations have been underlyed by this objective measure, especially for inhomogeneous image areas for which blurriness effect is quite noticeable to the observer. That confirms the relevance of the proposed measure and that the local analysis plays an important role in visual judgment. Then, we have computed for each image the global mean value of local differences. This enables us to classify the two sets of filtered images, from the smallest (value near 1) to the highest (value near 0) global value, relatively to the original image. Results obtained are given in table 1.

mandrill	(a) – (a)	(d) – (a)	(h) – (a)
mean of differences	1.00	0.66	0.73
highest mean value	1	4	3
	(j) – (a)	(m) – (a)	(p) – (a)
mean of differences	0.58	0.65	0.74
highest mean value	6	5	2

pears	(a) – (a)	(d) – (a)	(h) – (a)
mean of differences	1.00	0.81	0.73
highest mean value	1	2	5
	(j) – (a)	(m) – (a)	(p) – (a)
mean of differences	0.72	0.77	0.79
highest mean value	6	4	3

Table 1: *Images classification from the less distant image to the most distant image to the original image for which mean value of local differences is equal to 1.00.*

mandrill	(a)	(d)	(g)
entropy value	16.20	15.51	15.99
less different	1	5	3
	(j)	(m)	(p)
entropy value	15.14	15.91	16.09
less different	6	4	2

pears	(a)	(d)	(g)
entropy value	13.08	12.80	12.95
less different	1	5	4
	(j)	(m)	(p)
entropy value	12.46	13.12	13.04
less different	6	2	3

Table 2: *Images classification from the nearest to the most different color entropy value to the original image.*

3.2. Image quality descriptors

In order to analyze the quality of an image, relatively to an another one, we propose firstly to compare their color distribution relatively to the spatial distribution, secondly to compare their spatio-color distribution relatively to the variability of local contrast.

In previous works [2], we have shown that it is more relevant to analyze the spatial distribution of colors than analyzing only color distribution in terms of global dispersion. That is the reason why, we propose to compute the color entropy to compare images. Next we have classified the two sets of filtered images, from the nearest, to the most distant color entropy value, to the original image. Results obtained are given in table 2.

mandrill	(a)	(d)	(g)
mean of variances	108.36	66.40	101.58
less different	1	5	2
	(j)	(m)	(p)
mean of variances	27.47	99.68	100.48
less different	6	4	3
pears	(a)	(d)	(g)
mean of variances	16.90	15.33	37.26
less different	1	2	5
	(j)	(m)	(p)
mean of variances	13.78	42.45	37.08
less different	3	6	4

Table 3: Images classification from the nearest to the most different local variance value to the original image. (A gamma correction is applied to local variances values to enhance the most noticeable local contrasts.)

Another way to analyze the spatio-color distribution of an image is to compute the local variance of each pixel relatively to its neighborhood. This measure is all the more useful that it enables also to define the degree of homogeneity of each image area [4], as we can see in figures 1 and 2. On these images the smallest local variance values are displayed in black, meanwhile the highest local variance values are displayed in white. These values are computed according to the following formulae :

$$\sigma^I(x,y)^2 = \frac{1}{Card\,V(x,y)} \sum_{(x',y')\in V(x,y)} \omega(x',y') \cdot \sum_{c=L^*,a^*,b^*} \left(c^l(x',y') - \mu_c^l(x,y)\right)^2$$

Then, we have classified the two sets of filtered images, from the nearest, to the most distant mean local variance value, to the original image. Results obtained are given in table 3.

4. Conclusion and discussion

The two sets of images, used to illustrate this article, have been classified by a group of ten observers, firstly according to their color rendering, from the best to the worst, secondly according to their perceived quality, from the sharpness to the blurriness. Results obtained are given in table 4. They demonstrate that, according to perceived attributes considered, the perceived quality of an image may vary noticeably. This result is more perceptible for images *pears* than for images *mandrill*). These classifications can be compared to those given previously. They confirm that the perceived quality of filtered images depends of several attributes which can not be gathered in one image descriptor. They confirm also that even if each of proposed descriptors is itself relevant of several perceived aspects, none of these descriptors can not be used independently of the others.

mandrill	(a)	(d)	(g)
color rendering	1	5	3
sharpness to blurriness	1	6	3
	(j)	(m)	(p)
color rendering	6	2	4
sharpness to blurriness	6	2	4
pears	(a)	(b)	(c)
color rendering	1	6	3
sharpness to blurriness	1	3	6
	(d)	(e)	(f)
color rendering	5	2	4
sharpness to blurriness	4	2	5

Table 4: Images classification given by observers. 1) Images are ranked from the best to the worst in terms of color rendering of image elements. 2) Images are ranked from the sharpness one to the blurriness one.

Our aim is now to analyze the weight of each of these descriptors, relatively to the others, according to observers judgment. The most difficulty to overcome will be to rely these descriptors to memorized reality attributes.

5. References

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