# A New Quantification Method under Colorimetric Constraints

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## Abstract

In this work, we present a color quantification method based on the matrix of local pallets and colorimetric criteria. The proposed method extracts a set of one-dimensional colors resulting from image partitioning. Image windowing depends upon the image variance, which gives information about color dispersion. The color sets are then used to generate the rows of the local pallet matrix that will be used as a smaller image but more interesting. The selection of the principal pallet used to quantify the color image is accomplished on the local pallet matrix by computing the histogram. From this histogram we extract recursively the most important color. Then, we eliminate its n most similar colors. To avoid conflict between equi-frequent colors we use EMD distance that determines the best color by matching the results. Finally, image is quantified by replacing each pixel's color by the nearest color from the final pallet.

## Introduction

Color image quantification is the principal tool used to reduce the complexity of digital image. The complexity reduction is done with a minimal visual distortion. Color quantification can also be seen as a compression process with loss. At first, quantification was used to reproduce 24 bit images that can contain more than 16 millions of colors, on graphics hardware with limited number of simultaneous colors. Even though graphics hardware of more than 24 bit is becoming more common, color quantification still maintains its practical value. It lessens space requirements for storage of image data and reduces transmission bandwidth requirements in multimedia applications.

Since first applications of quantification were especially used to display color images on color output devices with reduced pallet size and low cost, quantification algorithms had to respect two conditions. On the one hand, the visual distorsion between the original image and the quantified one must be as small as possible. On the other hand, the quantified image has to be computed at the time the image is displayed. This makes computational efficiency of high importance.

A first approach for defining a color table consists in fixing the set of representative colors $\{c_1,\ldots,c_K\}$ in order to cover a wide color spectrum. Then, we talk about the uniform quantification where the set of representative colors is predetermined[12,13] and still identical for every image to be quantified. It is very clear that if the number of final colors is reduced, this type of algorithm gives less interesting results than a quantification that build a set of representative colors adapted to every image. These algorithms are called adaptive quantification algorithms. They divide the multi-set $(C,f)$ associated to the image in a set $\{(C_1,f),\ldots,(C_K,f)\}$ of elements and then associate to every multi-set $(C_i,f)$ a representative color.

Numerous authors approached this problem by global approach.[2,3,5,6,8] These allow to preserve the most frequent colors without taking into account weakly present colored constituents but perceptually important. The figure1 shows that by using a global method and extracting from it only the most frequent colors (region B), we can lose very important information (represented by the peak A on the figure). Other methods suggested resolving this difficulty through local approaches.[1,9] We join this last type of method through a technique leaning on the matrix of local pallets.[10] A local pallet corresponds to a set of N colors in a window of the image with N the size of the final pallet.

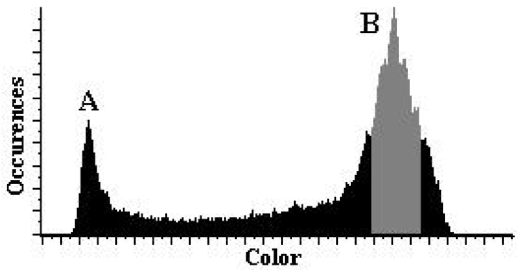



*Figure 1. A candidate histogram*

Local pallets recovery allows to know the influence of a color in the image. The reduction of the matrix of the local pallets is made by introducing a colorimetric constraints which allow to avoid keeping two very similar colors within the final pallet. Finally, to resolve the conflicts, which can remain during the color fusion, we called a metric allowing to calculate the distance between two sets having different cardinalities.

The remainder of this article is organized as follow: Section 2 present the proposed approach followed by the experimental results. We finish by giving some conclusions.

## Approach

Let us consider an image *I* associated to the multi-set *(C, f)*, where *C* represent all the colors present in an image and *f (c)* the occurrence number of the color *c* in the image *I*. Let us take the following notations: $p_i$ the local pallet *i* of the matrix of the local pallets, $P_F$ the final pallet. *Nb_color* represents the number of colors of the final pallet.

The image *I* is divided into a number of windows which directly depends on statistical characteristics of the image and the number of colors to be kept. On one hand, the number of colors to be kept allows to fix a minimal threshold of the window used. Indeed, if the user asks for a final pallet of size 16 for example, the window size must not be lower than 8 (knowing that the size of windows is a power of 2). Choosing a window of size 4 imply that all the colors are going to be used in the MPL, what really complicates the task. Finally this size of window is governed by the following equation:

$$Nb\_color * 4 \leq f^2 \qquad (1)$$

where *f* is the windows size.

On the other hand, the computation of the image global variance allows to choose between two possible sizes of window deducted from the conditions described previously. The variance is marginally calculated on the three-color plans of the image. Furthermore, a high value of the variance indicates us that a high number of colors exist in the image and consequently windows should be the smallest possible and vice versa. To choose between both sizes of window, we defined a threshold called *V*. its value depends on experiments. For example for *Nb_color=256*:

*If variance* $\geq$ *V then,* $f = 16$*;*

*else* $f = 32$*; end if ;*

Once the window size is known, we calculate for each of them a local histogram. This allows us to select *Nb_color* most frequent colors to create a line of the matrix of the local palettes. The fact of having local pallets gives us a rich information about the most present colors but without passing besides - as in certain global methods - colors having less important histogram peaks. The matrix of local pallets is considered as a new image representing the most significant colors of the image *I*. we calculate its histogram to know the occurrence of each color.

Clearly, the problem settles as the elaboration of a measurement system between two colors sets with different cardinalities. A minimum distance between the final pallet and the histogram of the matrix of the local pallets is looked. The distribution metrics[11] proposed by Rubner[12] goes into this problematic. It gives a generic but exploitable solution within the framework of the quantification. We make here a contribution to this problem by a pyramidal approach; the conflict resolution is made thanks to the EMD distance, proposed by Rubner.

### a. Histogram Reduction By Hierarchical Classification

The classical algorithm of hierarchical classification agglomerates elements among them or elements to sets of elements following their respective nearness. The agglomerate tree produced is then split at a given height to generate the wished classification. We thus work on a competitive agglomerate notion. In every stage, the distances between an element and the other elements or sets should be estimated. To do it, if one wants to respect the nature and the depiction of the image, only the color distance established in a perceptually exact space is acceptable. The competition between elements is then managed according to their appearance frequencies then by agglomerating elements that are close.

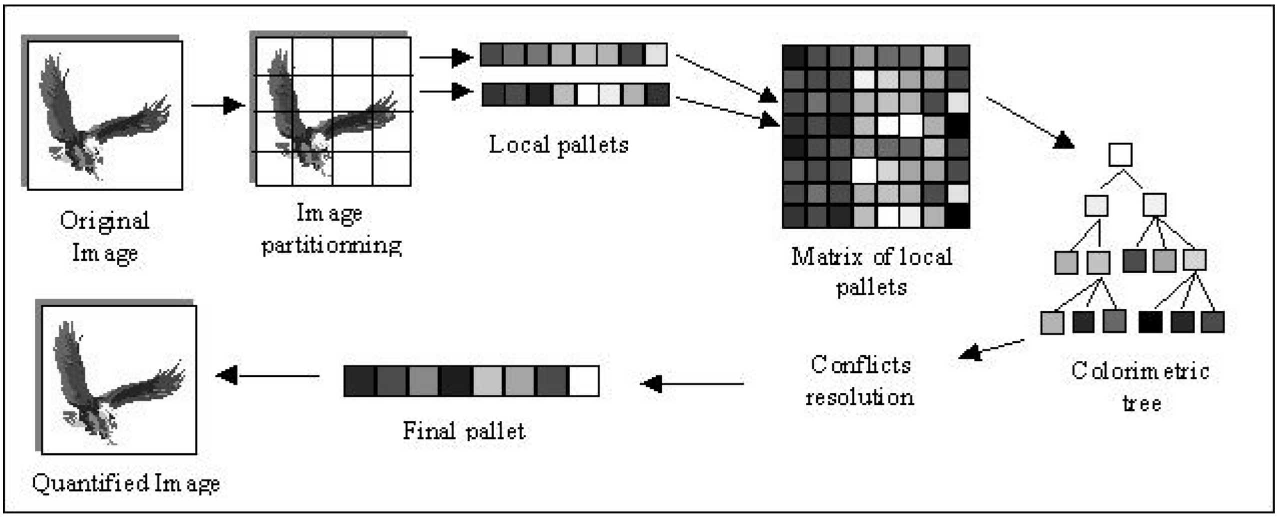



*Figure 2. Synoptic scheme*

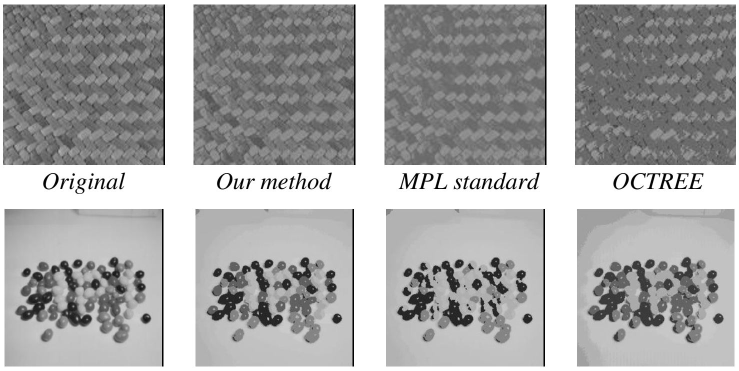



*Figure 3. Image quantification*
*Image Fabrics (7133 colors quantified into 4 colors)*
*Image JellyBeans (8808 colors quantified into 16 colors)*

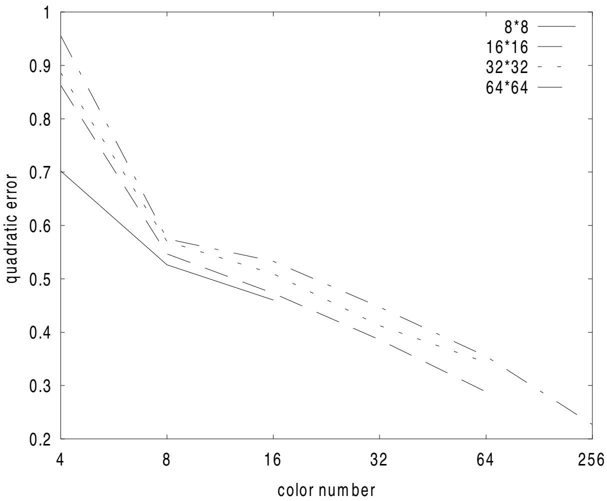



*Figure 4. Quantification error with different windows sizes*

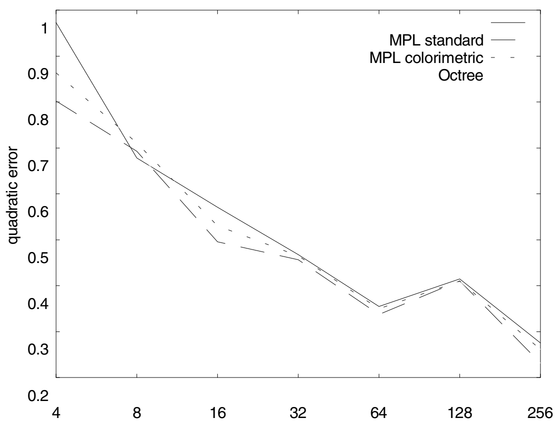



*Figure 5. Quantification error with different methods*

**b. Resolution of the Conflicts**

When several candidates having the same frequency exist in the histogram, they represent so much final solution. Only one minimizes the distance between the histogram of the matrix of the local pallets and the pallet generated by this candidate. The evaluation of this measure is made thanks to the EMD distance (Earth Mover's Distance). It allows measuring a distance between two histograms independently of their size. The selected candidate will then be agglomerated with his color neighbors in the tree.

## Experimentation

The proposed algorithm is tested on various image categories (landscape, painting, medical). The images presented on the figure 2 show that the algorithm gives very good results. In spite of the enormous color loss, the image remains of good quality and especially exploitable. The experiments have shown that the window size influences the result quality (figure 3). Indeed, by using the smallest window, the results are better.

Experimentation has shown that our method gives very good results and respects the colorimetric aspect of the image.

## Conclusion

The most effective methods in quantification are often based on tools such as Fuzzy C-Mean, which do not allow to master the classification outputs. We propose a hierarchical approach. The interest of this method lies in the partitioning possibility by criteria imposed by the user. In the same way, this method does not depend on color organization or on a uniform quantification of the color space. The agglomeration of the similar colors allows to avoid a redundancy in the final pallet and to optimize the efficiency. The information of textures is preserved by the local first order statistics. This type of approach improves the visual aspect of the image.

This algorithm has given good results compared with standards one but still need improvement in the implementation in order to increase its computation speed.

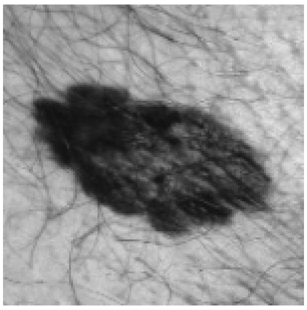
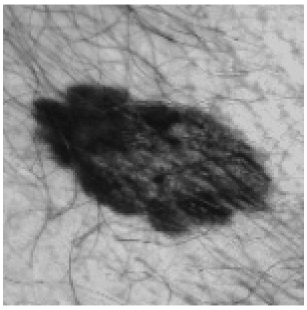


Image of dermatological lesion (18000 colors)



Quantified Image in 256 colors

Landscape image (90000 colors)

Quantified Image in 400 colors

Sunflower image (77000 colors)

Quantified Image in 256 colors)

Painting image (+100000 colors)

Quantified Image in 256 colors

*Figure 6. Some quantification results*

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