Effective Digital Image Colors Reduction/Quantization Method

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Abstract

In the current research work, a method to reduce the color levels of the pixels within digital images was proposed. The recent strategy was based on self organization map neural network method (SOM). The efficiency of recent method was compared with the well known logarithmic methods like Floyd-Steinberg (Halftone) dithering and Octtrees (Quadtrees) methods. Experimental results have shown that by adjusting the sampling factor can produce higher-quality images with no much longer run times, or some better quality with shorter running times than existing methods. This observation refutes the repeated neural networks is necessarily slow but have best results. The generated quantization map can be exploited for color image compression, classification, or to edit the color palette for different image graphical applications.

Keywords: Quantization, SOM neural network algorithm, Color reduction, Classification.

طريقة فعالة لتكميم/تخفيض ألوان الصور الرقمية

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الخلاصة

في البحث الحالي تم اقتراح طريقة لتخفيض المستويات اللونية للعناصر الصور الرقمية. الستراتيجية الحالية تعتمد على طريقة الشبكة العصبونية ذاتية تنظيم التحويل.كفاءة الطريقة الحالية تم مقارنتها مع الطرق المعروفة مثل طرق تأثير فلويد-ستينبيرغ والثمانية. النتائج العملية بينت بأنه وبتعديل عامل الاعتيان يمكن إنتاج صور بوضوحية عالية مع وقت ليس بالطويل أو الحصول على نوعية جيدة بوقت قصير ومقارنة مع الطرق الموجودة.من خلال ملاحظة النتائج تبين لنا إن الشبكات العصبونية هي بطيئة ولكن تعطي نتائج جيدة. الخريطة التكميمية الناتجة يمكن استخدامها في تطبيقات الضغط, التصنيف, او تحرير الصفيحة اللونية لمختلف الصور الرقمية.

1. Introduction

Color quantization (also known as color reduction) is sampling of three-dimensional (3-D) color spaces (such as RGB or Lab) which results in a discrete subset of colors known as a color codebook or palette. It is extensively used for display, transfer, and storage of natural images in Internet-based applications, computer graphics, and animation [1].

Therefore, the color reduction is an important technology especially in real world digital image processing. A digital image is usually described by a set of pixels distributed in two dimensional grids. A true-type color image consists of more than 16 million different colors in a 24-bit RGB color space. Thus, it is easier to understand and process an image with a low number of colors. It is preferable that images are quantized to as low number as possible.Many techniques have been developed for color quantization. They are classified in major two categories. The first class of algorithms is based on splitting algorithms in which the color space is divided into disjoint regions by consecutively splitting up the color space. For every region, a color is chosen to represent it. In general, the major disadvantage of these algorithms is to ignore the interrelationship between neighboring color regions in the process of split [2].

To resolve the problem mentioned above, the second class of algorithms is proposed which depends on clustering analysis. Artificial neural network is a very powerful tool to resolve clustering [2].

In general, the algorithms based on clustering analysis have better quantization results than ones based on splitting scheme. But it has much higher complexity and cost much more running time than the latter ones.

2. Related works

In recent years, many advanced classification approaches, such as artificial neural networks, fuzzy-set and expert system, have been widely applied for image classification. [3] presented a network that self-organizes to form an ordered map of an arbitrary sequence of n-dimensional patterns. The ordered map results in a structural representation of a learned sequence which can be used to recognize and classify sequences of patterns. In [4] image colors are projected into a small set of prototypes using self-organizing map (SOM) learning. The techniques used for improving classification accuracy and some important issues affecting classification performance are discussed. It is of great help in this domain. Classifiers such as neural networks have increasingly become important approaches because of their robustness and their easy availability in almost any image processing [5].

3. The standard SOM Algorithm

The aim is to learn a *feature map* from the spatially *continuous input space*, in which the input vectors live, to the low dimensional spatially *discrete output space*, which is formed by arranging the computational neurons into a grid [4]. Figure1 show standardSOM image quantization scheme.

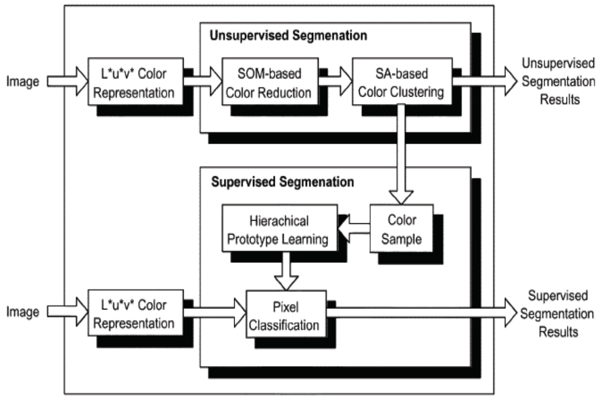


Figure 1- Image segmentation system based on SOM neural networks [4].

3.1 Kohonen Neural Networks

Kohonen neural networks [6, 7] and [8, sections 3.4 and 4.4] are a form of self-organizing neural network which define a mapping from a subset of $\mathbf{R_n}$ to $\mathbf{R_m}$, where m×n is the dimension of the network. In other words, an m-dimensional abstraction is made of the n-dimensional input space.

The Kohonen neural network architecture provides both kinds of learning generalization described by [9]. Structural generalization is provided by the fact that all updates to the network apply to a neighborhood of adjacent neurons, which correspond to similar color states. These updates are made most strongly at the central best-matching neuron, and more weakly at the edges of the neighbourhood. Temporal generalisation is provided by the activity mechanism, which is used to propagate 'good' and 'bad' values back in time to recently visited states. One difficulty with the Kohonen approach is that values are recorded for neurons, rather than directly for color states. During the early phases of training, there is considerable movement of neurons through the color space. Consequently, the color state corresponding to a neuron can change with time, making learned values incorrect. In the next section we describe techniques for dealing with this problem, so that the networks nevertheless provide an effective learning method.

3.2 The Learning Algorithm

Initially, the weight vector was set along the main diagonal of the color space, which provides a good first approximation to the input. At each training step, we find the 'best' weight vector ($\boldsymbol{R_i,G_i,B_i}$) corresponding to the input data point($\boldsymbol{R,G,B}$). This vector is then updated by moving it closer to the input, giving the neural network a better "t" to the data points:

$(R_i,G_i,B_i)=\alpha\times(R,G,B)+(1-\alpha)\times(R_i,G_i,B_i)$...(1)

Here **α** is a parameter which is initially **1**, and decreases with time. Kohonen [10, p 133] suggests decreasing **α** linearly, but we have found that results are improved and training time is decreased if **α** decreases exponentially down to a minimum of **1/32** .

As usual, we consider the network to be slightly "elastic" in that when a weight vector is updated, the neighboring vectors are also moved. Specifically, there is a neighborhood on radius ***r***, which decreases with time, and for $i-r \leq j \leq i+r$ (and $0 \leq j \leq 255$), we update the vectors in the neighborhood by:

$(R_j,G_j,B_j)=\alpha\,\rho_{(i;j;r)}(R,G,B)+(1-\alpha\,\rho_{(i;j;r)})(R_j,G_j,B_j)$

where: $\rho_{(i;j;r)}$ is equal to **1** if **i=j**, decreasing as **|i-j|** increases, down to **0** when **|i-j|=r**.

We have found by experience that, as is the case with ***α***, the values of ***r*** used significantly affect performance. The best results for this application are obtained when ***r*** decreased exponentially from 32 at cycle 0 until ***r*** becomes less than 2 at cycle 86, i.e. the value of ***r*** at cycle ***t*** is given by:

$$r = e^{-0.0325t} \quad \ldots(3)$$

This definition of ***r*** is combined with the following definition of $\rho_{(i;j;r)}$:

$$\rho_{(i,j,r)} = 1 - \left(\frac{|j-i|}{\lfloor r \rfloor}\right)^2 \quad \ldots(4)$$

Where |**r**| is the integer part of **r**.

Proposed method description

In General, color image quantization scheme involved on the following steps [3]:

- Sampling the original image for color statistics.
- Choosing a color map based on the color statistics.
- Mapping original colors to their nearest neighbors in the color map.
- Quantizing and rendering the original image.

4. proposed method implementation

Our proposed technique description is implementation but with some parameters modification as illustrated in section **3.2** of SOM algorithm. The implementation showed in the following algorithm:

*1- **Initialization** –Initialize network in range (0,0,0) to (255,255,255) and set parameters (**initnet**)*

*2- Unbiased network to give byte values 0..255 and record position **i** to prepare for sort (**unbiasnet**)*

*3- Output color map (**writecolormap**)*

*4- Insertion sort of network and building of netindex[0..255] (to do after unbias) (inxbuild), small value entry is now in position **i***

5- Search for RGB values 0..255 (after net is unbiased) and return color index bestd = 1000; biggest possible dist is 256×3

6- Search for biased RGB values:

- *finds closest neuron (min dist) and updates **freq***
- *finds best neuron (min dist-bias) and returns position*
- *for frequently chosen neurons, $freq_i$ is high and $bias_i$ is negative*
- *$bias_i$=**gamma**×((1/**netsize**)- $freq_i$)*

*7- Move neuron **i** towards $biased_{r,g,b}$ by factor **alpha** (alter-single)*

*8- Move adjacent neurons by pre-computed **alpha**×(1-((i-j)^2/[r]^2)) in $radpower_{[|i-j|]}$ (alter-neigh)*

9- Start Learning Loop

Please see (appendix A) for more clarification about algorithm arguments.

5. Tested Results

The proposed algorithm is compared with color quantization methods in [2] and [10] in terms of statistical measures MSE, PSNR.

Let us consider a data set P_X consisting of N input vectors. If p_i -P_X is an input vector, and $p'i$ the corresponding quantized vector, (1) and (2) are used to measures of the statistical color quantization errors [2].

$$MSE = \frac{1}{N}\sum_{i=0}^{N}(p_i^{/} - p_i)^2 \ldots\ldots\ldots\ldots(4)$$

$$PSNR = 10\log\left(\frac{3\times255\times255\times N}{\sum_{i=0}^{N}(p_i^{/} - p_i)^2}\right)\ldots\ldots.(5)$$

The set of the images are used whose information is described in Table 1 and showed in Figure 1. For the comparison reason, these images are respectively quantized to 16, 32, 64, 128 and 256 unique colors. The value of the number of the neurons convergences to 16, 32 64, 128 and 256, respectively is adjusted.

Table1- information of the tested images.

Images	Size (pixel)	Color number	Source
Palm	274×285	69095	[2]
Alley	244×162	61390	
Parrots	285×188	70493	[3]
Sky	281×187	54375	

(a) Ally image **(b) Palm image**

(c) Parrots image **(d) sky image**

Figure 1- original tested images.

From Tables 2,3,4,5 (**QL** is quantization level, **CSF** is color sampling factor and **ET** is elapsed time=1/1000 sec.), it is obviously that the final quantization results based on our suggested scheme give best results subjectively. Figure 2 show objectively the best results associated with the results in these tables for 128 color level and color sample factor =1.

Table 2- Alley image results.

QL	CSF	MSE	PSNR	ET
8	1	0.11	33.65	705
	2	0.11	33.65	602
16	1	0.09	34.52	1244
	2	0.09	34.52	1082
32	1	0.08	35.03	2358
	2	0.07	35.61	2057
64	1	0.08	35.03	3469
	2	0.08	35.03	2193
128	1	0.07	35.61	2541
	2	0.07	35.61	1359
256	1	0.07	35.61	4813
	2	0.07	35.61	2528

Table 3- Palm image results.

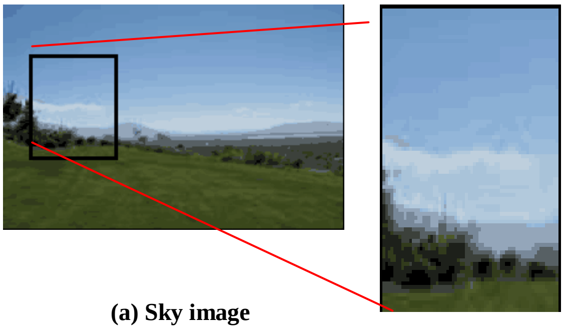
QL	CSF	MSE	PSNR	ET
8	1	0.14	32.60	1373
	2	0.14	32.60	1140
16	1	0.05	37.08	2478
	2	0.05	37.08	2100
32	1	0.04	38.04	4649
	2	0.04	38.04	4029
64	1	0.04	38.04	4210
	2	0.04	38.04	3772
128	1	0.04	38.04	5098
	2	0.04	38.04	2778
256	1	0.04	38.04	9683
	2	0.04	38.04	5192

Table 4- Parrots image results.

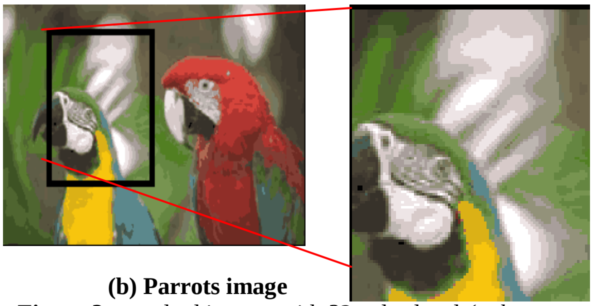
QL	CSF	MSE	PSNR	ET
8	1	0.17	31.76	942
	2	0.18	31.51	801
16	1	0.11	33.65	1698
	2	0.11	33.65	1451
32	1	0.08	35.03	3178
	2	0.08	35.03	2741
64	1	0.07	35.61	3716
	2	0.08	35.03	3136
128	1	0.07	35.61	2459
	2	0.06	36.28	1896
256	1	0.05	37.08	6586
	2	0.07	35.61	3504

Table 5- Sky image results.

QL	CSF	MSE	PSNR	ET
8	1	0.06	36.28	741
	2	0.06	36.28	1577
16	1	0.05	37.28	1354
	2	0.05	38.04	2963
32	1	0.04	38.04	2554
	2	0.04	38.04	3712
64	1	0.04	38.04	2415
	2	0.04	38.04	3114
128	1	0.04	38.04	1675
	2	0.04	38.04	1342
256	1	0.04	38.04	5977
	2	0.04	38.04	3170

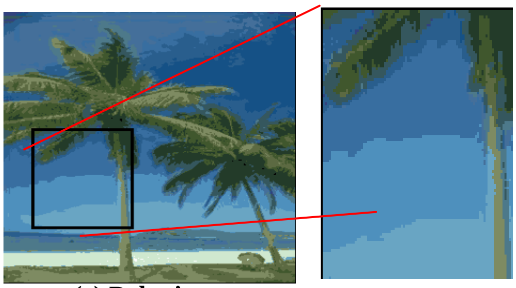


(a) Sky image



(b) Parrots image

Figure 2 - resulted images with 32 color level.*(to be continue in the next page)*



(c) Palm image

(d) Alley image.

Figure 2 resulted images with 32 color level.

6. Conclusions

We presented color quantization algorithm for mapping 24-bit colour image to less than 8-bit color based on self-organizing Kohonen Neural Networks. With limited sampling, proposed method can produce output which is slightly better than that of the other methods presented in [2] and [10], while running more quickly. If more pixels are sampled, very high quality images are obtained, with almost half theme a mapping error, and with no contouring or other artifacts. The algorithm uses very little space (on l8k Bin addition to the space used to store the input image) the color map produced by our algorithm has useful continuity properties: similar colors are usually quantized to similar representatives, and adjacent representatives represent similar colors. The seeing properties allow the quantized image to be compressed.

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