A NOVEL IMAGE RE-INDEXING BY SELF ORGANIZING MOTOR MAPS

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ABSTRACT

Palette re-ordering is a well known and very effective approach for improving the compression of color indexed images. If the spatial distribution of the indexes in the image is smooth, greater compression ratios may be obtained. As known, obtaining an optimal re-indexing scheme is not a trivial task. In this paper we provide a novel algorithm for palette re-ordering problem making use of a Motor Map neural network. Experimental results show the real effectiveness of the proposed method both in terms of compression ratio and zero-order entropy of local differences. Also its computational complexity is competitive with previous works in the field.

***Index Terms*—** Image coding, Neural networks, Multimedia computing, Entropy, Color, Data compression.

1. INTRODUCTION

Colour-mapped images make use of an index map to store the different involved colours maintaining for each pixel the location of the corresponding index. Local index redundancy can be considered to improve the compression performances of any compression technique. Re-indexing techniques try to find the optimal reordering avoiding to consider all possible color indexing (M! for an image with M colors). The existing re-indexing algorithms may be classified into two main groups: colors and indexes based. These approaches are devoted to obtain respectively colour and index similarity ([1]). The bottleneck of this group of solutions is the intrinsic inefficiency to numerically optimize the palette re-indexing. To overcome this problem different heuristics have been proposed ([2, 3]).

In this paper we propose a method to solve the re-indexing problem by means of Motor Maps (MM) neural network. The ability of MM to find an optimal solution without requiring the knowledge of the underlying model has been crucial in this context. Major details about MM network design and related applications can be found in [4]. The overall performances have been evaluated by considering the same repository used in [1] that contains synthetic and natural images with different size and number of colours. Experimental results show effective results if compared with previous results in the field. It represents a good trade-off between overall performances and computational complexity.

The paper is structured as follows. Section 2 introduces the re-indexing problem, while MM reindexing technique is presented in Section 3. Experimental results are presented in Section 4. Conclusions are drawn in Section 5.

2. PROBLEM FORMULATION

The re-indexing problem can be stated as expressed in ([1,3]). Let I be an image of $m \times n$ pixels, and M be the number of distinct colors. I can be represented as $I(x, y) = P(I'(x, y))$, where $P = \{S_1, S_2, \ \dots \ , S_M\}$ is the set of all the colors in I, and I' is a $m \times n$ matrix of indexes in $\{1, 2, \ \dots \ , M\}$ with M typically equal to 16, 64, 256, or 512. An image represented in such a fashion is called *indexed image* (or *colour mapped image*) and P is its *palette*. Most of the compression engines proceed by coding the data attacking the local spatial redundancy. For indexed image, an ordered scan of the indexes in I' named $p_1, \dots \ , p_{m\times n}$ is usually performed. The residual entropy of local differences can be considered to estimate the overall "energy" of the signal. The information needed to reconstruct the original image is:

i) the colour of pixel p_1 ;

ii) a table providing the correspondence between colours $S_1, S_2, \dots, S_M$ with index $i_1, i_2, \ \dots \ , i_M$;

iii) the set of differences:
$D(I') = \{d_{x,y} | x = 1, 2, \dots, m \, y = 1, 2, \dots, n\}$ where each $d_{x,y}$ is a local difference obtained by considering some specific patterns as better specified below.

Information theory states that any lossless scheme to encode the set of differences $D(I')$ requires a number of bits per pixel (bpp) greater or equal to the zero-order entropy of the statistical distribution of $D(I')$. The related entropy of the sequence of differences is one of the main parameters that guides the proposed optimization process. If indexes $i_1, i_2, \ \dots \ , i_M$ are ordered so as to produce an almost uniform distribution of values $d_{x,y}$ the entropy value will be large. Conversely, a zero-peaked distribution in $D(I')$ gives a lower entropy value. Hence, finding an optimal indexing scheme is a crucial step for any lossless compression of indexed images.

3. THE MM RE-INDEXING ALGORITHM

3.1. MM for re-indexing

The proposed algorithm is based on the ability of the MM neural network to learn the "features" of the input pattern (a lightness factor of a still image, in this case) providing an appropriate output stimulus. We propose to use a MM which provides, during the learning process, a palette shape clustering for searching (in the output stage of the network) the optimum indexing scheme. The learning process has been modified respect to the classic algorithm in order to adapt itself to solve the palette re-indexing issue. The unsupervised learning mechanism of MM can be adapted to general purpose systems. In our case the overall approach can be described by the following steps.

Step 1. The topology of the MM has been established by making use of some heuristic considerations so that a lattice structure of 64×64 neurons appears suitable for this kind of applications. It is interesting to note that the self auto-organizing structure of the MM provide an automated mechanism for which the neurons always losing in the extended WTA algorithm, will be *pruned* and not involved in the learning process. The MM during the learning process, after a transient, will use only the neurons needed according to the input image shape and complexity. Let N be a number of neurons of the MM. Each neuron is composed by an input weight $w_i^{in},\ i = 1, \ldots, 64 \times 64$ with $w_i^{in} \in [0, 1]$ and output weight $w_i^{out},\ i = 1, \ldots, 64 \times 64$ and a variable $b_i,\ i = 1, \ldots, 64 \times 64$ which stores the average increasing of the reward function. The range of the w_i^{out} values is $[1, \ldots, M]$. In our case, the following reward function has been chosen:

$$Reward = -\left(\sum D(I')\right)^2 \tag{1}$$

The above reward is strictly proportional to the zero-order entropy of the differences matrix $D(I')$. Moreover, the selection of the above reward function leads the MM to find an optimum palette index scheme which minimize the entropy of the image and then the related compression ratio. Regarding the output stimulus $f(t)$ produced by the MM during the learning phase, in this work, it has been forced equal to w_i^{out}. The w_i^{out} will be equal to a random index generated during the learning process when the corresponding neuron wins. Before to start the learning phase, the MM (both input layer and output layer) is initialized randomly. Before starting the learning phase, a palette pre-processing is applied, i.e. the corresponding lightness factor of the input colours are sorted in increasing order.

Step 2. Let Y the luminance vector computed starting from the palette P of the image I. In case of RGB color space, the luminance can be approximated by the lightness factor computed for each color $S_i(r_i, g_i, b_i)$ by using the well known expression:

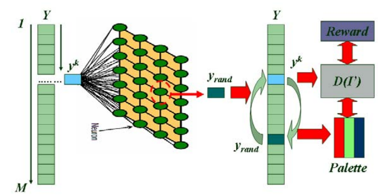


Fig. 1. New palette scheme provided by MM.

$$y_i = 0.299 r_i + 0.587 g_i + 0.114 b_i \quad i = 1, 2, \ldots, M \tag{2}$$

where M is the number of palette colors.

Step 3. Each element of the vector *Y*, normalized in the range $[0, 1]$, is fed to the input layer of the MM, one element at each iteration, searching the winner neuron i.e., the neuron which has the minimum value of the following distance:

$$d_i = |y^k - w_i^{in}| \quad i = 1, 2, \ldots, N; k \in [1, 2, \ldots, M] \tag{3}$$

The winner neuron provides an updating of the output stimulus *f(t)* which is, in this case, a new index y_{rand} (for the "winner" luminance) on the luminance vector i.e. a new index for the related colour on the corresponding palette performing also the related swaps on the indexes image. The new index is generated randomly in the range $[1, 2, \ldots, M]$. After the index updating, the new reward function can be computed updating only the elements in the associated matrix $D(I')$ which have been involved in the indexes swapping, in order to speed up the algorithm execution time. The $\Delta Reward$ will be computed as:

$$\Delta Reward \quad = \quad (Reward^{new} - Reward^{old})^2 \tag{4}$$

The average increasing of the reward function is weighted by the b_{win}^{new}:

$$b_{win}^{new} = b_{win}^{old} + \rho(\Delta Reward - b_{win}^{old}) \tag{5}$$

where ρ is a positive value related to the smoothing action.

Step 4. If the $\Delta Reward \geq b_{win}^{new}$ and the new current entropy (really the new current sum of absolute differences) is better than the already ones processed till now, the new index scheme will be accepted and the weights of the winner neurons will be updated:

$$w_{win}^{in}(t+1) \quad = \quad w_{win}^{in}(t) + \eta(y^k - w_{win}^{in}(t)) \tag{6}$$

$$w_{win}^{out}(t+1) \quad = \quad y_{rand} \tag{7}$$

where η is the learning rate factor. After that, the learning steps (from 2 to 4) is repeated until the stop criteria is verified. Conversely, the new index scheme will be rejected and the previous ones will be restored. Fig. 1 shows the MM re-indexing mechanism In the architecture of the MM proposed in this work, the neuron has not an adaptive neighboring and the learning rate remains constant during all the learning phase. The stop of the learning process is reached when the computed entropy is less or equal to a specific lower bound value or after a fixed number of epochs (an epoch is a number of cycles needed for presenting all the input patterns to neural network). For each re-indexed image, a log file shows the number of epochs performed for re-indexing the corresponding palette.

3.2. Algorithm parameters

As described before, the MM parameters are chosen according to trial-and-error policies as well as heuristic considerations. In particular, after several tests and analysis of the problem, we have chosen $\eta = 0.01$ and $\rho = 0.90$. Typical number of learning cycle k is in the range of $[350, 700]$ in almost all involved experiments. The set of differences $D(I')$ has been computed by using the local pattern configuration V_1 ([5]) expressed as:

$$D_{V_1}(I') = \{I'_{x,y} - I'_{x,y-1}\} \tag{8}$$

where x, y are the corresponding valid indexes in the original $m \times n$ image I.

3.3. Computational complexity

Let M the overall number of involved colours of an input image I having $N = m \times n$ pixels. The proposed technique requires a preprocessing phase devoted to the input colours according to their lightness factor. Each learning cycle have to compute the reward function, by considering just a single index swap in the matrix index $D(I')$. The overall computational complexity is $O(MlogM) + O(kNM)$ where k is the number of learning cycles. We remind that previously published works in the field of re-indexing of colour mapped images have been often also compared with respect to their time complexity but only considering the number of colours M. According to this criteria, the most effective and used methods have the following time complexity: $O(MlogM)$ for luminance order, $O(M^2logM)$ for Battiato's approach [3], $O(M^3)$ for Zeng's [2] and its modification [5], and $O(M^4)$ for Memon [6]. The proposed MM re-indexing is clearly one of the most effective methods especially when the above complexity is computed also considering the input image resolution (i.e. the number of involved pixels N).

4. EXPERIMENTAL RESULTS

In order to check the performances of the MM as palette re-indexing algorithm (called MMap), we propose the comparison between our method and the most important reordering methods ([2], [1], [3]). We don't use Memon's approach in our experiments because it is strongly limited by its high computational complexity ([1, 5]). For sake of comparison, the dataset used is the same of ([1]). It is organized in three groups: synthetic, a set of natural images also known as 'kodak' database, and a set of popular natural images. The last two sets contain quantized version of the same images with 256, 128 and 64 colours, respectively. We choose to present only results by considering non-dithered version of *Natural1* and *Natural2* groups because the performances (in terms of bpp) of any re-indexing technique are clearly affected by a slightly degradation due to the controlled 'noise' inserted by the specific applied dithering. As stated above, the first evaluation of a re-indexing scheme have to be done by using the residual zero order entropy of local differences $D(I')$ by using the pattern V_1. A useful comparisons of such values between the proposed method MMap and the others is reported in Table 1.

Table 2 reports the bits rate in terms of bpp (bit per pixels) obtained by lossless compression of the dataset after palette reordering by using JPEG2000[1], JPEG-LS[2], and PNG[3], respectively. The tables show also the size (in bpp) of the corresponding palette just to evaluate the relative impact on the overall results. By using all coding engines, the values of bpps of the proposed approach are considerable lower than the other methods, in some cases the differences are substantial. This trend is maintained independently from the number of colours and it does not change if we compare synthetic or natural images. All re-indexed images can be downloaded at the following web address:
http://www.dmi.unict.it/ iplab/MMap_reindexing/.

5. CONCLUSION AND FUTURE WORK

In this paper, we have described a technique that shows a good performance on the optimum palette scheme generation without any initial hypothesis on the palette index scheme or on the pixel distribution. In fact, it is interesting to note that a lot of palette re-indexing algorithm proposed in literature are based on the assumption that the differences of neighboring pixels of well-reordered images should follow a Laplacian distribution. This is in accordance with the JPEG-LS image coding standard, which also assumes a Laplacian model for the prediction residuals and, therefore, may provide a justification for the good performance of both methods. The MM algorithm does not need any hypothesis on the initial image's pixel distribution as well as on the re-ordered final image.

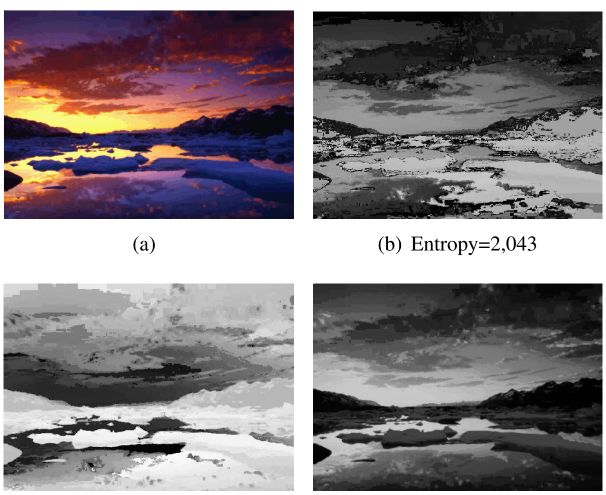
[1]FastStone vers. 2.6(B4),(www.FastStone.org)
[2]SPMG/JPEG-LS Encoder vers. 1.0
[3]The Gimp vers. 2.2.9

Images	**Random**	**Luminance**	**Zeng**	**mZeng**	**Battiato**	**MMap**
Synthetic	*2,795*	*2,516*	***2,073***	*2,078*	*2,125*	*2,078*
Natural1	*4,720*	*4,032*	*3,234*	***3,214***	*3,346*	*3,253*
Natural2	*5,497*	*4,902*	*4,045*	*3,977*	*4,208*	***3,868***

Table 1. Residual zero-order entropy of images before and after using the palette re-ordering methods.

	Type	**Random**	**Luminance**	**Zeng**	**mZeng**	**Battiato**	**MMap**
JPEG2000	**Synthetic**	*3,438*	*3,141*	*2,794*	**2,677**	*3,078*	*2,783*
	Natural1	*5,380*	*4,327*	*4,210*	**3,943**	*4,731*	*3,958*
	Natural2	*5,819*	*4,501*	*4,722*	*4,385*	*5,182*	**4,242**
JPEG-LS	**Synthetic**	*2,854*	*2,526*	*2,452*	*2,333*	*2,650*	**2,306**
	Natural1	*4,859*	*3,942*	*3,852*	*3,579*	*4,320*	**3,558**
	Natural2	*5,239*	*4,065*	*4,297*	*3,924*	*4,664*	**3,828**
PNG	**Synthetic**	2,705	2,595	2,375	2,404	2,315	**2,270**
	Natural1	*5,208*	*4,633*	*4,109*	*4,116*	*3,926*	**3,797**
	Natural2	*6,291*	*5,749*	*5,073*	5,123	*4,956*	**4,554**

Table 2. Lossless compression results in bit per pixel, obtained with JPEG2000, JPEG-LS, and PNG applied to the indexed images after using the palette reordering methods presented in the paper.



(a) (b) Entropy=2,043

(c) Entropy=1,774 (d) Entropy=1,730

Fig. 2. Different re-indexing schemes. (a) Colour image; (b) original indexes; (c) modified Zeng's re-indexing; (d) proposed approach.

6. REFERENCES

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