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A novel effective and efficient color image compression technique for cloud computing

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1. Introduction

AS the result of the IT evolution, there are more network applications and demands, particularly for multimedia. Nevertheless, those digital contents may increase the need for storage capacity and network bandwidth. Consequently, data compression is an essential and significant principle for those digital contents because of the smaller data capacity.

In general, Image compression schemes can be classified as lossy or lossless. Lossy compression models lower redundancy and irrelevancy through a series of transform in frequency domain to reconstruct the image with the minimum errors. Redundancy reduction eliminates duplication signals, and irrelevancy reduction abates visually insignificant signals [1]-[4]. Several lossy compressions, such as JPEG and JPEG2000, have been adopted. Lossless compressions, such as PNG and JPEG-LS, reconstruct the compressed images identically. Spatial domain is another model that is dissimilar to frequency domain, and generally employs VQ (vector quantization) in a lossy compression [5]-[13]. VQ is mainly applied to minimize the number of codewords of a codebook to approach the original image. Namely, an image compression occurs by reserving a codebook composed of some codewords and an index-table that catalogs the index-values rather than raw codewords [6]-[7]. Several VQ-based algorithms, such as LBG, SOM and HSOM and Tsai et al. [1], have been presented to design the codebook appropriately and efficiently. Moreover, the proposed ELSA technique also belongs to this classification.

LBG is fast and simple to implement, but has inconsistent coding, and is prone to becoming trapped in local optima [8]. An artificial neural network structure called Self-Organizing Map (SOM) applied to image compression can achieve an excellent result, but it is very time-consuming [9]-[11]. SOM trains the weights of several neurons, which it regards as codebook within specified training times. Since SOM gradually fine-tunes these neurons to derive global optima, it is named a full-search algorithm. Hierarchical Self-Organizing Map (HSOM) has been developed to decrease the time complexity of SOM [12]. Although HSOM divides the entire compression process into a few stages to simplify the large scale and accelerating compression, but typically yields slightly worse quality solutions than SOM.

As shown in Figure 1, an original image is first split into the smaller blocks according to parameter BlockSize, which represents how many pixels a block requires. Accordingly, some encoding methods such as LBG, SOM or HSOM are performed with those blocks to generate the codebook that consists of n (given by parameter *CodebookSize*) representative codewords. It is called compression that can conserve the codebook formed by encoding the image through Vector Quantization. On the other hand, to reconstruct an image from the codebook by Vector Remapping is denoted as decompression.

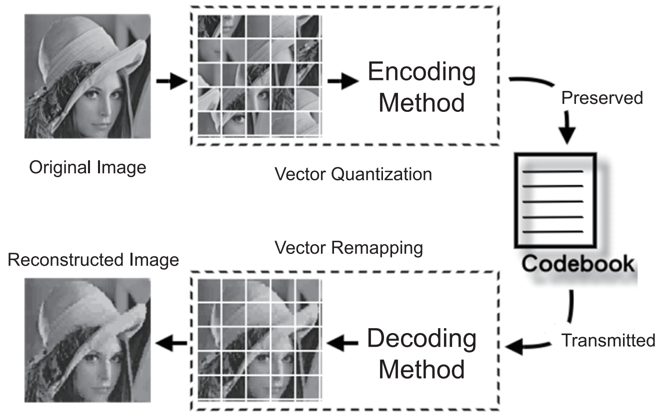

Figure 1. The image compression and decompression procedure.

This invention presents a new codebook design algorithm for image compression that adopts an Expanding-Tree technique and based on LBG called ELSA. In the first stage, ELSA utilizes an arbitrary expanding tree scheme and an effective estimation function to calculate the degree of distortion of each leaf, and thus may dynamically determine the rough representative vectors that form the initial codebook. In the final stage, a regular LBG is performed to train the initial codebook until a stopping criterion is met. The experimental results indicate that ELSA is with a quite better capacity than some existing well-known approaches.

2. Design Concept

As discussed earlier, although LBG is fast, it generates unstable clustering results because it randomly selects the initial codebooks. Moreover, although SOM and HSOM yield excellent result, they are much slower than other approaches. Accordingly, this work develops an image compression algorithm to combine the benefits of different techniques.

This section describes the principle of the proposed image compression algorithm, namely ELSA (or ET-LBG). First, the ELSA algorithm settles the initial codebook by “codewords tree expanding” where the codewords are dynamically produced by a modified LBG. “Leaf growth estimation” is then employed to determine which leaf is qualified and need to expand. Finally, “codebook convergence” is adopted to stabilize the codewords and upgrade the quality of each leaf using a regular LBG. The detailed implementation of ELSA has three stages, which are described as follows:

(1) Codewords tree expanding:

In this stage, LBG is applied with the codeword that has maximum distortion currently to output two new clusters as Figure 2 illustrated. In Figure 2(a), the initial and single codeword ‘A’ represents all vectors. In Fig. 2(b), as the previous codeword ‘A’ is with maximum distortion, it is thus split into two new codewords ‘A’ and ‘B’. In Figure 2(c), all existing codewords (e.g. the previous codewords ‘A’ and ‘B’) whose distortion is the biggest must be divided into new codewords ‘B’ and ‘C’. The incessant expanding is terminated until the desired number of codewords is obtained one by one.

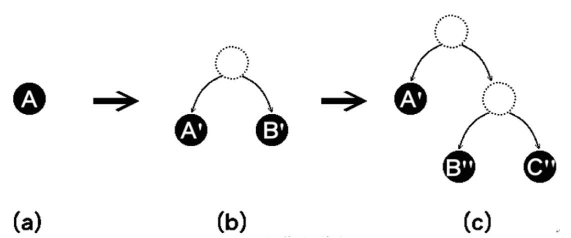

Figure 2. The expanding tree of codewords.

(2) Leaf growth estimation:

As we discussed the distortion in previous paragraph, ELSA determines which leaf (codeword) should expand based on a Total Square Error (TSE) measure as Eqn. (1):

$$TSE = \sum_{n=1}^{GroupSize} \sum_{d=1}^{BlockSize} [i(x_{n_d}, y_{n_d}) - \bar{i}(x_{n_d}, y_{n_d})]^2 \qquad (1)$$

$$\mathrm{MSE}(n) = \frac{\sum_{i=1}^{B(n)} \left[x_i(n) - c(n)\right]^2}{B(n)} \qquad (2)$$

In Figure 3, the MSE (noted in Eqn. 2) of group T is given by $(Lx3)/3/16=L/16$ and that of group W is $(Lx9)/9/16=L/16$. Nevertheless, we consider the distortion of these two groups should be different, because they cannot both be expressed by only one represented vector (the centered vector in each group). Thus, this phase employs a TSE function rather than the original MSE function. In Figure 3, the TSE of group T is $(Lx3)=3L$, and that of group W is $(Lx9)=9L$. As a result, group W has a larger TSE than group T, meaning that group W is allotted more codewords than group T so as to express vectors as appropriately as possible.

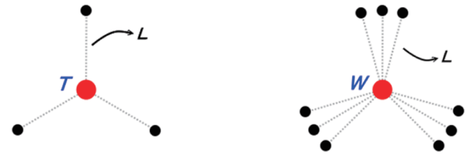

Figure 3. Two 16-dimensional vector groups that have different distortion. (a) Vector group T consists of 4 vectors and has the same radius L (b) Vector group W consists of 8 vectors and has the same radius L.

(3) Codebook convergence:

After deriving the initial codebook through stage one, a regular LBG is utilized for fine-tuning the quality of the final codebook. In each iteration, ELSA calculates the recent MSE value of that codebook, and compares it with the previous MSE value. The terminal criterion of ELSA is that the variation of the recent and previous MSE values are below a tiny and specified threshold (ε). The equation of MSE variation is given as follows:

$$\Delta D = |\,\mathrm{MSE}(t) - \mathrm{MSE}(t-1)\,|\,/\,\mathrm{MSE}(t)\,| \qquad (3)$$

where ΔD means the variation of MSE; |.| represents the absolute value measure, and t denotes the iteration.

3. Technical Development

Vector Quantization (VQ) is the most popular method in lossy image compression. An appropriate codebook design is an essential and helpful principle for Vector Quantization such as LBG, SOM and HSOM. The features of LBG are fast and simple, but the compression quality of LBG is not so stable. Even though SOM and HSOM yield the satisfied results, they are too time-consuming. This invention develops a new image compression method named ELSA, which employs an expanding leaf to determine the rough vectors (codewords) quickly and utilizes an LBG for quality improvement in the end. Experimental results reveal that ELSA outperforms LBG, SOM, HSOM and INTSOM in terms of computational cost and quality.

THE SYSTEM INTERFACE AND OPERATION PROCESSES

This invention presents a new effective and efficient image compression technique for cloud computing environment called ELSA, and its system interface and operation processes can be revealed as the following four figures (Figures 4-7). The system interface may comprise by three parts, namely input, execution and information. Figure 4 shows the start screen of the system. End users may click “Browse”button to read image file, and then click “open (開啟)”button to display image, as depicted in Figure 5. Moreover, end users can input the related parameters, as illustrated in Figure 6, and then continue to click “Run” button to conduct image compression and display its result as Figure 7 revelation.

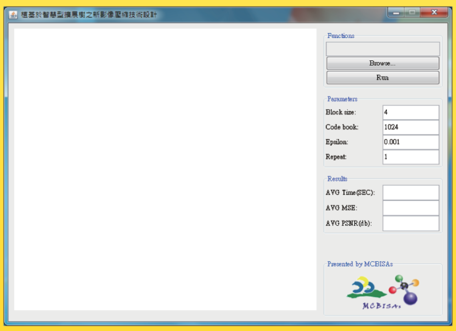

Figure 4. The start screen of the system.

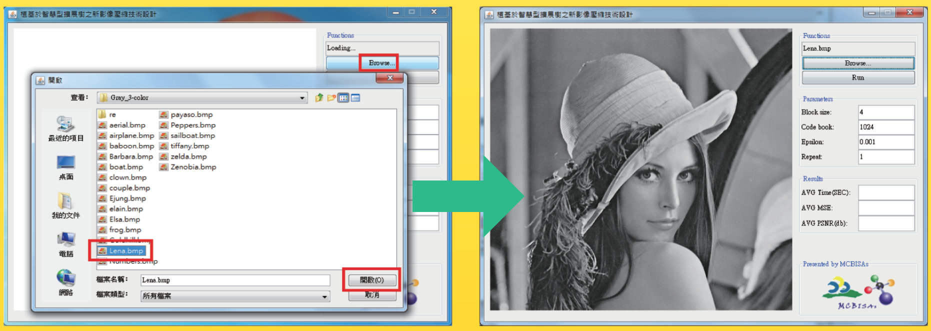

Figure 5. End users may click “Browse”button to read image file, and then click “open (開啟)”button to display image.

Figure 6. Parameters input

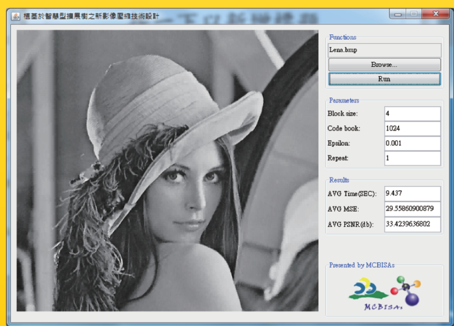

Figure 7. End users may click“Run” button to conduct image compression and display its result.

4. Technological Competitiveness

This invention presents a superior and efficient codebook design technique for image compression. The proposed technique, named ELSA, first employs an expanding tree principle to determine the initial codebook, and then adopts a regular LBG to stabilize and reinforce the initial codebook. Notably, although a smaller codebook size yields a higher compression ratio, it is not worth considering since the resulting quality is too low to preserve the image. Experimental results demonstrate that the proposed ELSA performs quite better and has a far shorter computational time than LBG, SOM and HSOM.

The invention has the merits as follows:

- This invention can reduce the color image compression execution time, since ELSA utilizes an arbitrary expanding tree scheme and an effective estimation function to calculate the degree of distortion of each leaf, and thus may dynamically determine the rough representative vectors that form the initial codebook.
- This invention may increase fairly good color image compression quality (with excellent peak signal-to-noise ratio; PSNR).
- This invention is simple and easily to implement.
- This invention outperforms the well-known existing techniques such as LBG, SOM, HSOM, INTSOM, LazySOM and commercial software Adobe Photoshop 9 in image compression quality comparison.
- This invention had obtained ROC and USA invention patents.

5. R&D Result

To verify the efficiency and quality of ELSA (ET-LBG), a series of 30 independent runs was undertaken for five well-known and one private image, which are illustrated in Figure 8. The algorithm was implemented in Java programming language using a personal computer with Intel Pentium4 3.2GHz CPU and 1GB RAM. Those images were tested at a size of 512x512 pixels, 256 levels, and the block size was 4x4, namely 16 dimensions per vector. Significantly, HSOM cannot process an image with a codebook size that is not a square number, so its results were discarded in some tests, given as N/A (Not Available). The experimental results are listed below. Figure 8 shows the 1024-codewords and 16-dimension images reconstructed by ELSA (a)Lena、(b)Airplane、(c)Peppers、(d)Boat、(e)Sailboat、(f)Ejung. Figures 9-10 reveal that ELSA (ET-LBG) has the best compression capability for images with large codebook sizes.

Codebook Size		128		256		512		1024	
Images	Method	PSNR	Timecost	PSNR	Timecost	PSNR	Timecost	PSNR	Timecost
Lena	LBG	29.549	5.18	30.447	10.32	31.262	18.26	32.109	29.96
	SOM	29.677	227.98	30.581	434.13	31.471	832.02	32.436	1624.91
	HSOM	N/A	N/A	30.642	67.58	N/A	N/A	33.022	132.73
	ET-LBG	**29.697**	**3.21**	**30.758**	**5.60**	**31.929**	**8.87**	**33.386**	**14.87**
Airplane	LBG	30.527	7.64	31.416	11.60	32.313	17.74	33.313	26.94
	SOM	31.115	229.30	32.124	424.82	33.156	831.29	34.319	1621.73
	HSOM	N/A	N/A	32.150	68.44	N/A	N/A	34.684	134.65
	ET-LBG	**31.173**	**3.15**	**32.306**	**5.46**	**33.542**	**8.65**	**35.029**	**14.86**
Peppers	LBG	29.650	5.31	30.441	9.83	31.197	16.66	31.980	25.89
	SOM	29.777	227.66	30.600	436.20	31.390	828.78	32.305	1620.84
	HSOM	N/A	N/A	30.613	68.95	N/A	N/A	32.594	142.48
	ET-LBG	**29.798**	**3.09**	**30.712**	**5.29**	**31.660**	**8.76**	**32.698**	**14.04**
Boat	LBG	29.068	7.19	29.896	11.50	30.733	17.96	31.670	26.60
	SOM	**29.329**	223.80	30.238	429.68	31.214	824.28	32.281	1610.44
	HSOM	N/A	N/A	30.175	67.88	N/A	N/A	32.475	134.40
	ET-LBG	29.311	**3.21**	**30.326**	**5.37**	**31.425**	**9.07**	**32.688**	**14.76**
Sailboat	LBG	27.484	6.35	28.188	9.91	28.931	15.41	29.776	23.19
	SOM	**27.713**	231.38	28.500	434.88	29.334	837.35	30.298	1653.13
	HSOM	N/A	N/A	28.502	68.90	N/A	N/A	30.421	135.15
	ET-LBG	27.689	**2.97**	**28.564**	**5.18**	**29.484**	**8.71**	**30.543**	**14.21**
Ejung	LBG	31.542	5.48	32.587	10.60	33.576	18.41	34.623	28.88
	SOM	31.887	231.73	32.905	440.23	33.992	833.84	35.130	1678.81
	HSOM	N/A	N/A	32.95	67.83	N/A	N/A	35.461	135.76
	ET-LBG	**31.932**	**3.14**	**33.096**	**5.46**	**34.311**	**9.70**	**35.687**	**15.67**

Figure 9. Comparison of PSNR (dB) and time-cost (Second) of reconstructed images for the proposed ET-LBG (ELSA) and other algorithms. The bold types denote the best results.

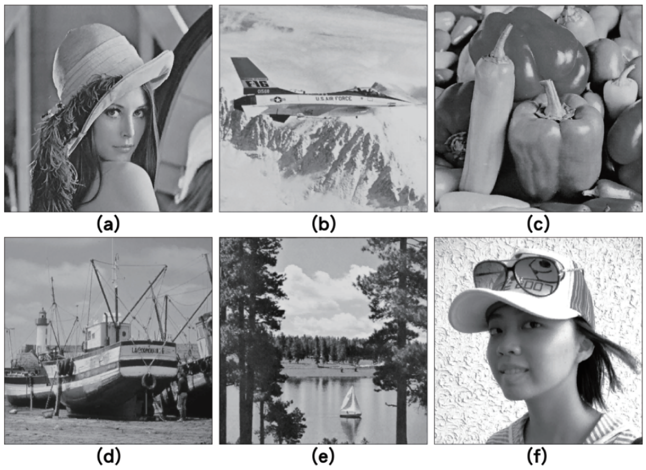

Figure 8. The 1024-codewords and 16-dimension images reconstructed by ELSA (a)Lena、(b)Airplane、(c)Peppers、(d)Boat、(e)Sailboat、(f)Ejung.

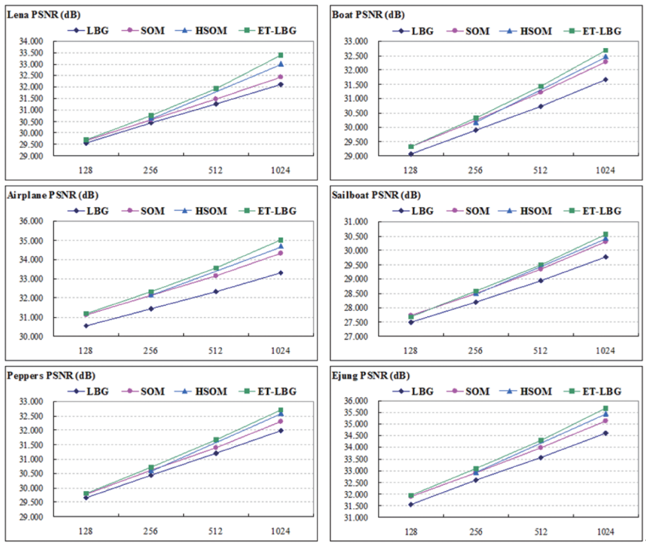

Figure 10. The trend chart of PSNR for the proposed ELSA (ET-LBG) and other approaches.

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