Gray Image Compression Using New Hierarchical Self-Organizing Map Technique

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Abstract

This work presents a new hierarchical self-organizing map (NHSOM) to solve image compression problem. NHSOM uses an estimation function to adjust numbers of maps dynamically, and reflects the distribution of data efficiently. Moreover, NHSOM takes splitting LBG to speed up the convergence of SOM, and reduce the training time. Our experimental results show that the proposed NHSOM has good capability in image compression compared with LBG, SOM, HSOM, Modified ART2 and EEMVQ.

1. Introduction

Various multimedia data in popular Internet and personal communication networks improve the content of websites, thus enhancing the user experience. Consequently, modern Internet applications require a high volume data to accommodate the large number of images. Image compression represents the process of data reduction based on sufficient conditions to express certain image information. Hence, efficient data compression techniques not only save storage space, but also accelerate the transmission time.

Numerous image compression techniques evolve from vector quantization (VQ). Various VQ techniques such as LBG, SOM, have been developed in recent decades to design codebooks efficiently [1]-[2]. However, LBG obtains its initial codebook randomly, producing unstable results and possibly falling into local optima. SOM updates the weights of code-vectors by gradually training them, which is a time consuming step. Some approaches including Hierarchical Self-Organizing Map (HSOM) and modified Resonance Theory Network (Modified ART2) attempt to reduce the time complexity [3]-[4]. HSOM has a lower time complexity than SOM, but cannot reflect the distribution of vectors owing to the restriction in the number of neuron nodes. Modified ART2 can efficiently express the distribution of vectors, but has a high clustering error rate and execution time.

This investigation presents a SOM-based new gray image compression approach called New Hierarchical Self-Organizing Map (**NHSOM**). NHSOM uses an estimation function to adjust numbers of maps dynamically, and reflects the distribution of data efficiently. In addition, NHSOM takes splitting LBG to speed up the convergence of SOM, and reduce the training time. Furthermore, the number of data vectors and the execution time both decrease during the learning process.

2. Literature review

The basic concepts of VQ are first introduced. Several well-known VQ techniques, namely LBG, SOM, HSOM and Modified ART2, are described, and their merits and drawbacks are outlined. Finally, measures of the image quality are introduced.

Vector Quantization (VQ), which is mainly applied to design codebooks, is a widely-employed lossy compression technique that can decrease the compression rate and preserve good quality after compression. An N×N gray image is first divided into n×n blocks, forming a block set X, which is transformed into code-vectors, as $X = \{x_1, x_2 \dots x_{n \times n}\}$. The codebook M comprises m code-vectors, e.g. $M = \{m_1, m_2 \dots m_k\}$, where m_k denotes a code-vector. A code-vector represents an index-value in the index-book. When transmitting images in the network, only the codebook and the index-book need to be transmitted, rather than the original image, thus reducing the storage space and time.

The LBG algorithm assigns code-vectors in the codebook by continuously calculating the distance of the training dataset until the average distortion is smaller than the input threshold [1]. The simplicity of the LBG algorithm means that it can obtain the codebook efficiently. However, selecting an initial codebook randomly may cause the algorithm to fall into a local optimum, possibly making the final result unstable.

Kohonen developed a Self-Organizing Map (SOM) in unsupervised neural networks in 1980 [5]. SOM utilizes the concept of "neighborhood", in which neurons neighboring the winning neuron are also activated. SOM typically generates better results than LBG. However, SOM takes full search to compete with the training data set, so has a fairly high time complexity.

SOM has been demonstrated to have good image

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compression capabilities, but has a high time cost due to the need to compare with the distance of each data vector with the corresponding code-vector, and the continuous learning and training processes. Lampinen has proposed a multilayer hierarchical SOM method which employs a hierarchical scheme to decrease the number of training data sets, thus reducing the time cost [6].

Hierarchical SOM (HSOM), presented by Barbalho in 2001, is first applied to image compression. HSOM utilizes a top-down approach to split the neurons, and composes a tree codebook. The generation of this tree scheme depends on two parameters, namely the numbers of levels (*ln*) and sub-neurons (*ns*). HSOM has advance a helpful method to solve the problem of time complexity in SOM but two issues are arisen at the same time. The first one is that the number of split neurons is fixed. This leads to a situation which the data distribution can't be expressed effectively. Another one is that the sub-neurons are derived from its parent neuron. This may make the sub-neurons fall into local optima.

ART2, presented by Carpenter in 1987, can handle continuous data [7]. Natalija later proposed Modified ART2, which can also handle in image compression, and which can also utilize a hierarchical scheme [4].

The human eye can generally judge the quality of a processed image, but not very objectively. Some objective measures are available to verify the quality of a compressed image. For instance mean square error (MSE), signal/noise relation (SNR) and Peak Signal-to-Noise Ratio (PSNR) are generally used, and are formulated as follows.

$$\text{MSE} = \frac{1}{M * N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left[\hat{I}(x,y) - I(x,y)\right]^2$$

$$\text{SNR} = 10\log_{10} \frac{\frac{1}{M * N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left[\hat{I}(x,y)^2\right]}{MSE}$$

$$\text{PSNR} = 10\log_{10} \frac{255^2}{MSE}$$

3. The proposed NHSOM algorithm

The NHSOM algorithm can be illustrated as follows:

Algorithm NHSOM

Input: Data(X_i), N, *level_num*, l=1, τ , initial neighborhood, initial learning, number of epoch

Output: CodeBook(Clusters)

Begin

```
SOM(Data, N^l); //Utilize SOM to train N^l nodes
Cluster();
while (l != level_num)
  for (j=0; j< N^l; j++)
    estimate Sub_Size_j by Eqn. (1), Eqn. (2) and Eqn. (3);
  endfor
  for (j=0; j< N^l; j++)
    while (jst node's split number < Sub_Size_j)
      Find out S_max in split number of jst node; /* Find out
        maximum S_j in current split number of jst node */
      Split S_max node into two new nodes (w_new1 and w_new2)
        by Eqn. (4);
      train w_new1 and w_new2 by LBG, training data belong to
      S_max node;
      Cluster();
      Let w_new1 and w_new2 instead of position of S_max node;
      delete S_max node;
    endwhile
  endfor
  for (j=0; j< N^l; j++)
    SOM(Data_j, Sub_Size_j); //Fine tuning Sub-Map of N^l
    nodes by SOM
    Cluster();
  endfor
  l +=1;
endwhile
Output CodeBook; // size of CodeBook is equal to N^l
clusters
```

End

Notably, the above mentioned Eqn. (1), Eqn (2), Eqn. (3), and Eqn. (4) in NHSOM algorithm may be revealed as follows:

$$\overline{D}_j = \frac{\sum_{i=1}^{Sample\_num_j} \left(x_i - w_j\right)}{Sample\_num_j} \tag{1}$$

$$S_j = \frac{\overline{D}_j^{\,\tau} * Sample\_num_j^{(1-\tau)}}{\sum_{j=1}^{N} \left(\overline{D}_j^{\,\tau} * Sample\_num_j^{(1-\tau)}\right)} \tag{2}$$

$$Sub\_Size_j = S_j * N^l \tag{3}$$

$$w_{new1} = w_{max} + (1+\delta) \tag{4}$$
$$w_{new2} = w_{max} + (1-\delta)$$

Where $\overline{D}$ represents error rate, x denotes training vectors, w is the weighting value of neurons, $Sample\_num_j$ represents the data numbers of neuron j. An evaluation equation is proposed to judge the size of split number of jth node as Eqn. (2), where N represents the number of neurons, τ denotes a digital number, Sub_Size_j is the split numbers of neuron j, l represents the level of current. Moreover, Eqn. (4) depicts splitting S_{max} node into two new nodes (w_{new1} and w_{new2}), where w_{new} denotes the weighting value of new neuron, w_{max} represents the weighting value of S_{max}, δ is a value between 0 and 1.

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4. Experiment results

The experiment comprising quality of compressed images and time cost of the proposed NHSOM algorithm were verified. The experiment was performed on a personal computer with an Intel Pentium 4, 3-GHz and 512 M RAM. Three gray Lena, Toys and Pepper images were used. The test blocks were 4×4 and 8×8, and the test codebook sizes were 64, 100, 256 and 1024. For paper length limitation, there were only Figure 1 and Tables 1-2 demonstrate the quality of compressed images and time cost of the proposed NHSOM and some existing approaches including LBG, SOM, HSOM, Modified ART2 and EEMVQ [8] with 4×4 and 8×8 test blocks and 64, 100, 256 and 1024 test codebook sizes. Experiment results indicate that the proposed NHSOM performs better than LBG, SOM, HSOM, Modified ART2 and EEMVQ and can compress images effectively. In addition, the time cost of the proposed NHSOM is lower than LBG, SOM, HSOM, Modified ART2 and EEMVQ.

4. Conclusion

This paper has presented NHSOM for efficient and effective codebook design. Moreover, NHSOM solves the defect in HSOM in which the data distribution is unknown. In the first stage, a smaller codebook is set for training with SOM, and then a rough codebook is obtained. The number of code-vectors is reduced during the learning process, thus reducing the execution time. In the second stage, clusters with bigger distortion rates than average insert a new code-vector, thus decreasing the distortion rate. Experiment results indicate that the proposed NHSOM performs better than LBG, SOM, HSOM and Modified ART2 and can compress images effectively. Furthermore, the time cost of the proposed NHSOM is lower than LBG, SOM, HSOM, Modified ART2 and EEMVQ.

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Table 1: Comparison of the quality of compressed images (PSNR) for the proposed NHSOM and some existing approaches by gray Lena with 8×8 blocks

Method / Size of CB	LBG	SOM	HSOM	Modified ART2	EEMVQ	NHSOM
64	25.72	**26.678**	26.513	23.378	26.365	26.557
100	26.459	**27.378**	27.317	24.038	26.692	27.349
256	28.384	28.761	29.134	26.443	28.032	29.29
1024	33.129	31.356	32.982	33.398	30.585	34.016

Table 2: Comparison of the time cost (in second) for the proposed NHSOM and some existing approaches by gray Lena with 4x4 and 8×8 blocks

Size of CB	64		100		256		1024	
Method \ Size of Block	4x4	8x8	4x4	8x8	4x4	8x8	4x4	8x8
LBG	231	211	412	372	812	799	1122	1026
SOM	273	246	432	386	1123	976	4488	3897
HSOM	71	59	82	80	131	123	279	246
Modified ART2	119	53	116	54	114	53	114	50
EEMVQ	24	23	28	27	43	42	59	51
NHSOM	46	43	62	61	93	88	185	176

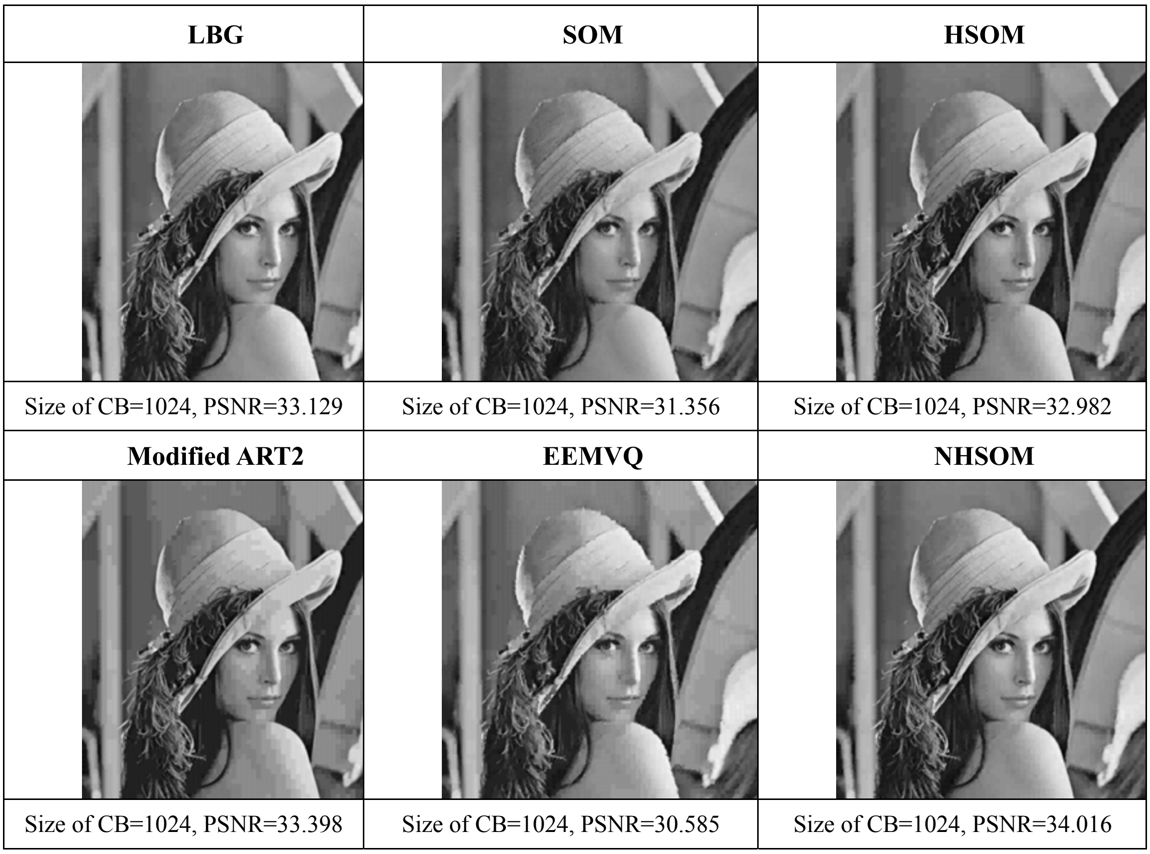

Fig. 1. Comparison of the quality of compressed images for the proposed NHSOM and some existing approaches by gray Lena with 8x8 test blocks.

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