Color Image Compression Using Spread Grey-Based Neural Networks in the Transform Domain

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Abstract

In this paper, a new Grey-based Competitive Learning Network (GCLN) for Vector Quantization (VQ) and Spread GCLN (SGCLN) for color image compression in the Discrete Cosine Transform (DCT) and Mean value / Difference value Transform (MDT) domains are proposed. A spread-unsupervised scheme based on the competitive learning neural network using the grey theory is proposed so that on-line learning and parallel implementation is feasible. In the GCLN, the grey theory is applied to a two-layer modified competitive learning network (MCLN) in order to generate optimal solution for VQ. In accordance with the degree of similarity measure between training vectors and codevectors, the grey relational analysis is used to measure the relationship degree among them. The color image information transformed by DCT or MDT operation was separated into RGB 3-plane mean value and detail coefficients. Then the detail coefficients for each plane were trained using the proposed SGCLN method to generate the VQ codebook. The experimental results show that promising codebooks can be obtained using the proposed GCLN and SGCLN for color image compression in the transform domains.

Keywords: *Color image compression, Grey theory, Competitive learning networks, Discrete cosine transform, Mean value / difference value transform.*

1 Introduction

A number of vector quatization algorithms for image compression have been proposed over the years [1-7]. The purpose of vector quantization (VQ) is to create a codebook such that the average distortion between training vectors and their corresponding codevectors in the codebook is minimized. Codebook design can be considered as a clustering process in which each training vector is classified to a specific class. The clustering process updates the codebook iteratively such that the average distortion between training vectors and codevectors in the codebook becomes smaller and smaller.

Neural networks with competitive learning demonstrated by authors capable of performing vector quatization [8-9]. In addition to the neural network-based techniques, the grey relational theory proposed in 1982 [10-13] was also incorporated into the codebook design in this paper. In the proposed grey-based competitive learning network (GCLN), the learning rule and stopping criterion of the original competitive learning neural network are modified to take into account the grey relational strategy. The problem of VQ is regarded as a minimization process of an object function. This object function is defined as the average distortion between the training vectors and the cluster centers represented by the codevectors in the codebook. The modified competitive learning network is simpler than that of the conventional competitive leaning network, and is constructed as a two-layer fully interconnected array with the input neurons representing the training vectors and output neurons representing the codevectors in the codebook.

Color images comprise three planes: red, green and blue. Thus, the most straight forward method to encode a color image by grey-based competitive learning networks is to split the RGB color image into 3 planes and compress them separately by treating each color component as a single gray-level image [14]. In this paper, the GCLN is modified to Spread GCLN (SGCLN) and applied to color image compression.

In the discrete cosine transform (DCT) or mean value / difference value transform (MDT) domain, this object function is defined as the average distortion between the training vectors in AC or detail coefficients to the cluster centers represented by the codevectors in the codebook. The training vectors, constructed by detail coefficients, are directly fed into the GCLN. The GCLN and SGCLN are demonstrated to have the capability of VQ in the transform domains.

The rest of this paper is organized as follows. Section II reviews the competitive learning networks. Section III presents the spread gray-based competitive learning networks for VQ. Section IV presents the DCT and MDT domains and GCLN. Experimental results are given in Section V. Finally, conclusions are drawn in Section VI.

2 Competitive Learning Network

A competitive learning network is an unsupervised network, which selects a winner based on similarity measure over the feature space. A proper neuron state is updated if and only if it wins the competition among all neurons. Many schemes for competitive learning networks have been proposed [15-16].

In the simple competitive learning network, the single output layer consists of cluster centers, each of which is fully connected to the inputs via interconnection strength. In the conventional competitive learning only one output unit is active at a time and the objective function is given by

$$J_c = \frac{1}{2}\sum_{j=1}^{c}\sum_{i=1}^{n} u_{i,j}\left\|\mathbf{x}_i - \boldsymbol{\omega}_j\right\|^2 \qquad (1)$$

where n and c are the number of training vectors and the number of clusters respectively. $u_{i,j}=1$ if $\mathbf{x}_i$ belongs to cluster j and $u_{i,j}=0$ for all other clusters. The neuron that wins the competition is called the winner-take-all neuron. Thus $u_{i,j}$ indicates whether the input sample $\mathbf{x}_i$ activates neuron j to be a winner. $u_{i,j}$ is given by

$$u_{i,j} = \begin{cases} 1 & if \left\|\mathbf{x}_i - \boldsymbol{\omega}_j\right\| \le \left\|\mathbf{x}_i - \boldsymbol{\omega}_k\right\|, \quad for \quad all \quad k \quad ; \\ 0 & otherwise \end{cases} \qquad (2)$$

The incremental $\Delta\boldsymbol{\omega}_j$ is given by [15-16]

$$\left\langle \Delta\boldsymbol{\omega}_j \right\rangle = -\eta\frac{\partial J_c}{\partial \boldsymbol{\omega}_j} = \eta\sum_{i=1}^{n}\left(\mathbf{x}_i - \boldsymbol{\omega}_j\right)u_{i,j},$$

$$j = 1,2,\cdots,c. \qquad (3.a)$$

where η is the learning-rate parameter. Although

Eq. (3.a) is written as a sum over all samples, practically it is usually used incrementally, i.e.

$$\Delta\boldsymbol{\omega}_j = \eta(\mathbf{x}_i - \boldsymbol{\omega}_j)\mu_{i,j}, \quad j = 1,2,\cdots,c. \tag{3.b}$$

The updating rule is given by

$$\boldsymbol{\omega}_j(t+1) = \boldsymbol{\omega}_j(t) + \Delta\boldsymbol{\omega}_j(t). \tag{4}$$

The modified competitive learning network (MCLN) has the same architecture as the conventional competitive learning network. It is an unsupervised competitive learning network using the modified competitive learning rule and stopping criterion. Similar to the standard competitive learning rule in Eqs. (3.b) and (4), the least squared error solution can be obtained by [9]

$$\boldsymbol{\omega}_j(t+1) = \begin{cases} \boldsymbol{\omega}_j(t) + \eta(\mathbf{x}_i - \boldsymbol{\omega}_j) & \textit{if} \ \|\mathbf{x}_i - \boldsymbol{\omega}_j\| \le \|\mathbf{x}_i - \boldsymbol{\omega}_k\|, \quad \textit{for all } k \ ; \\ \boldsymbol{\omega}_j(t) & \textit{otherwise} \end{cases}$$

(5)

The MCLN algorithm modifies only output neurons without updating the interconnection strengths. Instead of updating the interconnection strengths using the winner-take-all scheme in the conventional competitive learning network and for the purpose of simplifying the hardware architecture, the MCLN only modifies the output states (cluster centroids).

3 Spread Grey-Based Competitive Learning Network for VQ

Suppose an image is divided into n blocks (vectors of pixels) and each block consists of $\ell \times \ell$ pixels. A vector quantizer is a technique that maps the Euclidean $\ell \times \ell$-dimensional space $\mathbf{R}^{\ell\times\ell}$ into a set $\{\boldsymbol{\omega}_j, j = 1,2,...,c\}$ of points in $\mathbf{R}^{\ell\times\ell}$, called a codebook. It looks for a codebook such that each training vector is approximated as close as possible by one of the code vectors in the codebook. A codebook is optimal if the average distortion is at the minimum value. The average distortion $E[d(\mathbf{x}_i, \boldsymbol{\omega}_j)]$ between an input sequence of training vectors $\{\mathbf{x}_i, i = 1,2,...,n\}$ and its corresponding output sequence of code vectors $\{\boldsymbol{\omega}_j, j = 1,2,...,c\}$ is defined as

$$D = E[d(\mathbf{x}_i, \boldsymbol{\omega}_j)] = \frac{1}{n}\sum_{i=1}^{n} d(\mathbf{x}_i, \boldsymbol{\omega}_j) \tag{6}$$

The grey system is usually divided into several topics such as grey theory, grey mathematics, grey prediction, grey generating space, grey decision, and grey relational analysis. The grey relational theory addresses the measurement of similarity between training vectors and codevectors based on the grey relational space. Let $\mathbf{x}_i$ be a training vector and $\boldsymbol{\omega}_j$ be a codevector, then the grey relational coefficient between them is defined as

$$\gamma(\mathbf{x}_i, \boldsymbol{\omega}_j) = \frac{\Delta_{\min.} + \xi\Delta_{\max.}}{\Delta_{ij} + \xi\Delta_{\max.}} \tag{7}$$

where

$$\Delta_{\min.} = \min|\mathbf{x}_i - \boldsymbol{\omega}_j|$$

$$\Delta_{\max.} = \max|\mathbf{x}_i - \boldsymbol{\omega}_j|$$

$$\Delta_{ij} = |\mathbf{x}_i - \boldsymbol{\omega}_j|$$

and $0 < \xi < 1$ is the distinguished coefficient. The grey relational grade is given by

$$\gamma_{i,j} = \frac{1}{\ell \times \ell} \sum_{m=1}^{\ell \times \ell} \gamma\left(\mathbf{x}_i, \boldsymbol{\omega}_j\right) \quad (8)$$

where m is the dimension of the training vector $\mathbf{x}_i$ and the codevector $\boldsymbol{\omega}_j$.

In this paper, the grey theory is applied to a two-layer MCLN in order to generate optimal solution for VQ. The modified competitive learning rule is modified as

$$\boldsymbol{\omega}_j(t+1) = \begin{cases} \boldsymbol{\omega}_j(t) + \eta(\mathbf{x}_i - \boldsymbol{\omega}_j) & \text{if} \quad \gamma_{i,j} \geq \gamma_{i,k}, \quad \text{for all } k; \\ \boldsymbol{\omega}_j(t) & \text{otherwise} \end{cases}$$

(9)

We then map R, G, and B plane training vectors of a color image to the spread GCLN neuron array that compresses them separately by treating each color plane as a single gray-level image. Therefore, the spread GCLN based vector quatizer in the pth plane for the grey relational coefficient can be modified as

$$\gamma\left(\mathbf{x}_{i;p}, \boldsymbol{\omega}_{j;p}\right) = \frac{\Delta_{\min.} + \xi\Delta_{\max.}}{\Delta_{ij;p} + \xi\Delta_{\max.}} \quad (10)$$

where

$$\Delta_{\min.} = \min\left|\mathbf{x}_{i;p} - \boldsymbol{\omega}_{j;p}\right|$$

$$\Delta_{\max.} = \max\left|\mathbf{x}_{i;p} - \boldsymbol{\omega}_{j;p}\right|$$

$$\Delta_{ij;p} = \left|\mathbf{x}_{i;p} - \boldsymbol{\omega}_{j;p}\right|$$

the grey relational grade is given by

$$\gamma_{i,j;p} = \frac{1}{\ell \times \ell} \sum_{m=1}^{\ell \times \ell} \gamma\left(\mathbf{x}_{i;p}, \boldsymbol{\omega}_{j;p}\right) \quad (11)$$

and the grey-based competitive learning rule is modified as

$$\boldsymbol{\omega}_{j;p}(t+1) = \begin{cases} \boldsymbol{\omega}_{j;p}(t) + \eta(\mathbf{x}_{i;p} - \boldsymbol{\omega}_{j;p}) & \text{if} \quad \gamma_{i,j;p} \geq \gamma_{i,k;p}, \quad \text{for all } k; \\ \boldsymbol{\omega}_{j;p}(t) & \text{otherwise} \end{cases}$$

(12)

Then, the steps of codebook design using the spread grey-based competitive learning network are given as follows.

Step 1: Initialize the codevectors $\boldsymbol{\omega}_{j;p}\left(2 \leq j \leq c\right)$, learning rate η, maximum error (ME), total error (TE), and a threshold value ε.

Step 2: Input a training vector $\mathbf{x}_{i;p}$ and find the winner's codevector based on the maximum grey relational grade.

Step 3: Apply Eq. (12) to update the winner's codevector and set $TE = TE + \Delta_{ij;p}$.

Step 4: Repeat Step 2 and 3 for all input samples, then if $\left(ME - TE\right)/ME < \varepsilon$, go to step 5; otherwise replace ME content from TE, and go to Step 2.

Step 5: Complete the codebook design in the pth plane (p=1,2,3).

4 DCT and Mean Value/Difference Value Transform and GCLN

The discrete cosine transform [17] is the most widely used transform in many application, such as image processing, pattern recognition and image and video compression standards [18]. The DCT has extremely good compaction property. The forward and inverse 2-D DCT transform for an $N \times N$ image can be defined as:

Forward:

$$F(u,v) = \frac{4C_u C_v}{N^2} \sum_{i=0}^{N} \sum_{j=0}^{N} f(i,j) \cos\frac{(2i+1)u\pi}{2N} \cos\frac{(2i+1)v\pi}{2N}$$

(13)

Inverse:

$$f(i,j)=\sum_{i=0}^{N}\sum_{j=0}^{N}C_u C_v F(u,v)\cos\frac{(2i+1)u\pi}{2N}\cos\frac{(2i+1)v\pi}{2N}$$

(14)

where $F(u,v)$ are the DCT coefficients, $f(i,j)$ are the pixel value at (i,j) and $C_\tau=\frac{1}{\sqrt{2}}$ for $\tau=0$, $C_\tau=1$ for $\tau=1,2,3,\cdots N-1$.

The mean value / difference value transform is the simplest wavelet transform. Wavelet coding [19-20] plays an important role in data compression. The mean value / difference value transform is calculated as follows. Let us take an input sequence, {78, 52, 16, 28, 48, 56, 46, 30} as an example. As follows, we take mean value / difference value operation on these eight values, after three times transformation, the final coefficients are 44.25, -0.75, 21.5, 7, 13, -6, -4, and 8.

78	52	16	28	48	56	46	30
65	**22**	**52**	**38**	*13*	*-6*	*-4*	*8*
43.5	**45**	*21.5*	*7*	13	-6	-4	8
44.25	*–0.75*	21.5	7	13	-6	-4	8

The eight sampling values in the first row are treated as four pairs. In the second row, each bold value is the mean value of a pair in the first row: 65 = (78 + 52) / 2, 22 = (16+ 28) / 2, 52 = (48 + 56) / 2, and 38 = (46 + 30) / 2. In the third row, each bold value is also the mean value of the first two pairs in the second row. Analogously, in the fourth row, the bold value is the mean value of the first pair in the third row.

In the second row, each italic value is the difference value of a pair in the first row: 13 = (78 - 52) / 2, -6 = (16 - 28) / 2, -4 = (48 - 56) / 2, 8 = (46 - 30) / 2; we call these values by the name of detailed coefficients. Analogously, in the third row, the italic values are the difference values of the first two pairs in the second row. In the fourth row, the italic value is the difference value of the first pair in the third row.

The mean value / differential value transform is reversible and the eight original sampling values can be reconstructed step by step using the one mean value and seven detailed coefficients.

For a 2-D $N \times N$ image, the input image will be divided into nonoverlapping blocks of equal size. The DCT and mean value / difference value transform are applied to transform each block into DC or mean value and AC or detailed coefficients. Then the AC or detailed coefficients are fed into the GCLN algorithm for training vectors and generating better codebooks. In the decoder, indexes of codevectors are received to get AC or detailed information (codevectors). Then, the inverse DCT or mean value / difference value transform is used to reconstruct the image using DC or mean value and AC or detailed coefficients.

5 Experiment Results

The codebook design is the primary problem in image compression based on vector quantization. In this paper, the images reconstructed from the LBG、GCLN、discrete cosine transform + GCLN (named by DCT+GCLN) and mean value / difference value transform + GCLN (named by MDT+GCLN) methods are compared. The training vectors were extracted from 256×256 with 8-bit gray level real images, each of which is divided into 4×4 blocks to generate 4096 non-overlapping 16-D training vectors. Three codebooks of size 64, 128, and 256 were built by these training vectors. The resulting images were evaluated subjectively by the mean squared error (MSE) and peak signal to noise ratio (PSNR) that is defined for images of size N×N as

$$PSNR = 10 \log_{10} \frac{255^2}{MSE} \tag{15}$$

and

$$MSE = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(x_{ij} - \hat{x}_{ij} \right)^2 \tag{16}$$

where x_{ij} and $\hat{x}_{ij}$ are the pixel gray levels from the original and reconstructed images, and 255 is the peak gray level. In all experiments, $\xi = 0.5$ and $\eta = 0.1$. Table 1 shows the PSNR and MSE of the "Lena" and "Girl" images reconstructed from three codebooks of size 64, 128, and 256 designed by the LBG and the presented GCLN、DCT+GCLN and MDT+GCLN methods. From experimental results, the reconstructed images obtained from the presented GCLN are superior to those obtained from the LBG algorithm, and the performance of the presented DCT+GCLN and MDT+GCLN algorithms are significantly better than the GCLN algorithm.

In the color compression simulation, the color image information transformed by discrete cosine transform or mean value / difference value transform operation was separated into RGB planes DC or mean value and AC or detail coefficients. Then the AC or detail coefficients for each plane were trained using the proposed SGCLN methods to generate better codebook based on VQ. To show the reconstruction performance, the resulting images were evaluated by the average PSNR among three-color planes

$$PSNR_A = \frac{PSNR_R + PSNR_G + PSNR_B}{3} \tag{17}$$

where $PSNR_R, PSNR_G$, and $PSNR_B$ are the *PSNR* for red, green, and blue planes, respectively. The *PSNRs* of the "House", "Tree", "Girl", and "couple" images calculated are shown in Table 2, and their reconstructed images using the spread GCLN with 256 codevectoers each plane in the transform domain are shown in Figure 1. From the simulated results, the proposed DCT+SGCLN and MDT+SGCLN methods are simpler and produce better reconstruct image quality.

6 Conclusions

In this paper, an unsupervised parallel approach called Grey-based Competitive Learning Network (GCLN) for vector quatization and spread GCLN for color image compression in the discrete cosine transform and mean value / difference value transform domain (named DCT+SGCLN and MDT+SGCLN) have been proposed. Instead of iteratively updating the codebook in the conventional algorithm such as LBG, the codebook is updated just one time after the last iteration in the GCLN. It has been also demonstrated that the reconstructed images obtained from the GCLN are smoother than those obtained from the LBG algorithm in experimental results.

In the DCT or MDT domain method, the information transformed by discrete cosine transform or mean value / difference value transform operation was separated into DC or mean value and AC or detail coefficients. Then the AC or detailed coefficients are trained using the presented method to generate a better codebook in VQ. From the experiment results, the DCT+GCLN and MDT+GCLN methods are more promising than the GCLN method.

In the color image compression simulation, the presented DCT+SGCLN and MDT+SGCLN methods are simpler and produced better reconstructed image quality than SGCLN.

In addition, this proposed GCLN algorithm lends itself admirably to parallel implementation and has great potential in the real-time applications. However, the GCLN algorithm maybe converges to a local optimal codebook, which may not be the globally optimal solution. Consequently, we continue to investigate a genetic algorithm approach to obtain a near global optimal solution in the future.

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Table 1. PSNR and MSE of various gray images reconstructed by the LBG and the proposed GCLN and DCT+GCLN and MDT+GCLN algorithms.

Codebook Sizes / Algorithms	64		128		256	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
LBG	25.26	146.89	26.37	127.01	27.06	106.71
GCLN	26.09	160.01	27.23	123.11	28.84	84.89
DCT+GCLN	28.79	85.91	29.85	67.35	30.95	52.21
MDT+GCLN	28.88	84.25	30.18	62.46	31.03	51.34

(a) Lena

Codebook Sizes / Algorithms	64		128		256	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
LBG	27.68	109.62	28.51	91.60	29.69	77.09
GCLN	28.79	85.98	29.91	66.44	31.05	51.02
DCT+GCLN	31.73	43.71	32.64	35.40	33.80	27.11
MDT+GCLN	31.83	42.70	32.70	34.92	33.51	28.99

(b) Girl

Table 2. PSNRs of color images reconstructed by the Spread GCLN、DCT+SGCLN and MDT+SGFCN with 256 codevectors each plane.

Image/Algorithm (Plane)		R	G	B	Average
House	SGCLN	32.77	31.38	31.07	31.74
	DCT+SGCLN	35.25	34.18	33.45	34.30
	MDT+SGCLN	35.36	34.12	33.44	34.31
Tree	SGCLN	27.50	25.86	27.37	26.91
	DCT+SGCLN	29.59	28.14	29.24	28.99
	MDT+SGCLN	29.57	28.09	29.06	28.91
Girl	SGCLN	30.37	30.88	30.58	30.61
	DCT+SGCLN	33.18	33.55	32.62	33.12
	MDT+SGCLN	33.43	33.48	32.55	33.15
Couple	SGCLN	31.33	31.75	31.51	31.53
	DCT+SGCLN	33.93	34.39	34.04	34.12
	MDT+SGCLN	34.09	34.21	33.85	34.05

Figure 1. "Tree", "House", and "Girl", color test images and their reconstructed images using the spread GCLN with 256 codevectors each plane in the transform domain: (up row) original images, (down row) reconstructed images.