Color Image Compression Using Frequency-Sensitive Neural Networks with Wavelet Decomposition

Chi-Yuan Lin

Department of Electronic Engineering,

National Chin-Yi Institute of Technology, Taichung, 411 Taiwan, R.O.C.

Abstract

This paper present a modify Frequency-Sensitive Competitive Learning Network (FSCLN) with wavelet decomposition based on Vector Quantization (VQ) for color image compression. The goal is apply a spread-unsupervised scheme based on the neural networks so that on-line learning and parallel implementation for color image compression based on VQ in Wavelet Transform (WT) domain are feasible. In the FSCLN, each output neuron (codevector) incorporates a count of the number of times it has been the winner. The distortion measure used to determine the winner is updated to include the count number. The color image information was straightforward separated into RGB planes. Each plane is first decomposed into four subbands in the 1-level wavelet transform. Then the corresponding transformed coefficients are trained using FSCLN to form individual codebooks for each subband. The experimental results show that promising codebooks can be obtained using the presented FSCLN with wavelet decomposition for color image compression.

Keywords: Color image compression, Competitive learning networks, Wavelet transform.

頻率敏感的神經網路及小波分解用於彩色影像壓縮

林基源

國立勤益技術學院電子工程系

摘要

本篇論文，提出一個植基於向量量化技術之修正式「頻率敏感的競爭式學習網路」(FSCLN)及小波分解於彩色影像壓縮。其目的在於應用展延的非監督式神經網路，使得線上學習、平行計算是可行的。在FSCLN中，每一個輸出神經元(碼向量)其失真度量併計一獲勝次數已決定競爭勝利者。彩色影像則直接分解成R、G、B圖像，每一圖像分別經小波轉換成4個副頻帶(Subband)，然後將對應的轉換係數再經FSCLN以產生個別的編碼簿。經實驗模擬顯示，本篇論文所提方法具有良好效能。

關鍵字: 彩色影像壓縮、競爭學習網路、小波轉換。

I. Introduction

A number of vector quantization algorithms for data compression have proposed over the years [1-3]. The purpose of vector quantizaton 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 clutering 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 have been demonstrated capable of performing vector quantization [4-6]. A problem with the training procedure of competitive learning networks is that it sometimes leads to codevectors which are not distributed in an equiprobable manner [7]. The Frequency-Sensitive Competitive Learning (FSCL) [8] network is to overcome the limitations of the conventional competitive learning network. In Frequency-Sensitive Competitive Learning Network (FSCLN), the learning rule and stopping criterion of the FSCL network are modified to address the codebook design. 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 in a divided image to the cluster centers represented by the codevectors in the codebook. The frequency-sensitive competitive learning network is simpler than that of the FSCL 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 straightforward method to encode a color image by frequency-sensitive 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 [9]. In this paper, the FSCLN have is modified to Spread FSCLN and applied to color image compression.

In recent years, wavelet coding [10-11] plays an important role in image compression. The wavelet transform is identical to a hierarchical subband system. Basically, the wavelet transform decomposes an image into a set of sub-image blocks that are more stationary and hence provide better coding performance. A higher compression ratio can be achieved by the exploitation of quantizers adapted to the statistics of the sub-image blocks.

In this paper, the each color component is first decomposed into four subbands LL1, LH1, HL1, and HH1 in the 1-level wavelet transform. Then the corresponding transformed coefficients are trained using FSCLN to form individual codebooks for each subband. Computer simulations show that the FSCLN with wavelet transform based on VQ is promising for color image compression.

The rest of this paper is organized as follows. Section II reviews the competitive learning networks. Section III presents the spread FSCLN for VQ. Section IV presents the wavelet transform and FSCLN. Experimental results are given in Section V. Finally, conclusions are drawn in Section VI.

II. 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 [12-13].

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

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

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

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

The incremental $\Delta\boldsymbol{\omega}_j$ is given by [12-13]

$$\langle\Delta\boldsymbol{\omega}_j\rangle=-\eta\frac{\partial J_c}{\partial\boldsymbol{\omega}_j}=\eta\sum_{i=1}^{n}(\mathbf{x}_i-\boldsymbol{\omega}_j)u_{i,j},\quad j=1,2,\cdots,c. \tag{3.a}$$

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

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

The updating rule is given by

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

In the above equation, the η is the learning-rate parameter, and is typically reduced monotonically to zero as learning progresses.

Competitive Learning Algorithm

Step 1: Initialize the cluster centroids $\boldsymbol{\omega}_j(2\le j\le c)$, learning rate η, and interconnection strength $U=[u_{i,j}]$ between input training samples and neurons in the output layer.

Step 2: Update the interconnection strength in accordance with Eq. (2) with the competitive learning.

Step 3: Compute the states of all output neurons (cluster centroids) according to Eqs. (3) and (4).

Step 4: Repeat steps 2 and 3 for all input samples, and record the number of output neurons with changed state. If all states of output neurons are not changed, then go to Step 5.

Step 5: Output the final classification results.

III. Spread FSCLN 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 $\{\omega_j, j = 1,2,...,c\}$ 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 $E[d(\mathbf{x}_i,\omega_j)]$ between an input sequence of training vectors $\{\mathbf{x}_i, i = 1,2,...,n\}$ and its corresponding output sequence of code vectors $\{\omega_j, j = 1,2,...,c\}$ is defined as

$$D = E[d(\mathbf{x}_i,\omega_j)] = \frac{1}{n}\sum_{i=1}^{n} d(\mathbf{x}_i,\omega_j) \tag{5}$$

A modified distortion measure for the training process is defined as [8]:

$$d^*(\mathbf{x}_i,\omega_j) = d(\mathbf{x}_i,\omega_j(t)) \times c_j(t) \tag{6}$$

where $c_j(t)$ is the total number of times that code vectors ω_j has been the winner during training. The winning code vector at each iteration of the training process is the vector with the minimum d^*.

The FSCLN has the same architecture as the FSCL 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

$$\omega_j(t+1) = \begin{cases} \omega_j(t) + \eta(\mathbf{x}_i - \omega_j) & \mathit{if} \|\mathbf{x}_i - \omega_j\| \le \|\mathbf{x}_i - \omega_k\|, \quad \mathit{for\ all}\ k\ ; \\ \omega_j(t) & \mathit{otherwise.} \end{cases} \tag{7}$$

The FSCLN algorithm modifies only output neurons without updating the interconnection strengths. Instead of updating the interconnection strengths using the winner-take-all scheme in the FSCL network and for the purpose of simplifying the hardware architecture, the FSCLN only modifies the output states (codevectors). The steps of codebook design using the FSCLN are given as follows.

Step 1: Initialize the codevectors $\omega_j (2 \le j \le c)$, learning rate η, maximum error (*ME*), total error (*TE*), and a threshold value ε.

Step 2: Input a training vector $\mathbf{x}_i$ and find the winner's codevector based on the minimum d^*.

Step 3: Apply Eq. (7) to update the winner's codevector and set $TE = TE + \|\mathbf{x}_i - \boldsymbol{\omega}_j\|$.

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

Step 5: Complete the codebook design.

We then map R, G and B plane training vectors of a color image to the spread FSCLN neuron array that compresses them separately by treating each color plane as a single gray-level image. Therefore, the spread FSCLN based vector quatizer with within-class scatter matrix in the pth plane for the modified competitive learning rule can be modified as

$$\boldsymbol{\omega}_{j;p}(t+1) = \begin{cases} \boldsymbol{\omega}_{j;p}(t) + \eta(\mathbf{x}_{i;p} - \boldsymbol{\omega}_{j;p}) & \text{if } \|\mathbf{x}_{i;p} - \boldsymbol{\omega}_{j;p}\| \le \|\mathbf{x}_{i;p} - \boldsymbol{\omega}_{k;p}\|, \quad \text{for all } k \ ; \\ \boldsymbol{\omega}_{j;p}(t) & \text{otherwise} \end{cases} \tag{8}$$

Then, the steps of codebook design each plane using the spread FSCLN are given as follows.

Step 1: Initialize the codevectors $\boldsymbol{\omega}_{j;p}(2 \le j \le c)$, 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 minimum d^*.

Step 3: Apply Eq. (8) to update the winner's codevector and set $TE = TE + \|\mathbf{x}_{i;p} - \boldsymbol{\omega}_{j;p}\|$.

Step 4: Repeat Step 2 and 3 for all input samples, then if $(ME - TE)/ME < \varepsilon$, 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).

IV. Wavelet Transform and Spread FSCLN

The wavelet transform is a signal decomposition technique [14]. The mother function of wavelets, $\Psi(x)$, can be any function if it satisfies the following condition

$$\int_{-\infty}^{\infty} |\Psi(x)|^2 dx < \infty \tag{9}$$

Basically, most of the mother functions are derived from the scaling function $\Phi(x)$ which is any function satisfying the scaling equation

$$\Phi(x) = \sum_{i \in Z} c_i \Phi(2x - i) \tag{10}$$

For any integer j, we define vector space V^j as follows

$$V^j = span\{\Phi_i^j(x)\} \tag{11}$$

$$\Phi_i^j(x) = \Phi(2^j x - i), \quad i \in Z \tag{12}$$

If V^j satisfies the following four multiresolution analysis conditions
Condition 1: $f(x) \in V^j \Leftrightarrow f(2^{-j}x) \in V^0, \forall j \in Z$

Condition 2: $\bigcap_{i \in Z} V^i = \{0\}$

Condition 3: $\bigcup_{i \in Z} V^i = L^2(R)$

Condition 4: $\cdots \subset V^{-2} \subset V^{-1} \subset V^0 \subset V^1 \subset V^2 \subset \cdots$
it is easy to show that the mother function of wavelets is given by

$$\Psi(x) = \sum_{i \in Z} (-1)^i c_{1-i} \Phi(2x - i) \tag{13}$$

One of the most important characteristics of the wavelet transform is multiresolution. The wavelet transform converts the pixel values of images to wavelet domain, without lose any information in the spatial domain.

Vector quantization has been demonstrated to be an efficient method for image compression. The motivation for the proposed FSCLN with wavelet decomposition scheme is based upon the fact that the lower resolution wavelet coefficients hold more information and higher resolution wavelet coefficients hold less information. The basic idea is described as follows. The 1-level wavelet transform is first performed on the input image to generate the corresponding transformed coefficient. Then, the coefficients of each scale are trained separately to obtain an individual codebook. For example, the coefficients of LL1 and LH1 are divided into the blocks of size 2×2 and 4×4 from which two codebooks of size = 512, and 64 were built respectively. The coefficients of HL1 and HH1 are totally discarded since they rarely hold information, and are reconstructed by searching the best-matched codevectors from the codebook of LH1. The FSCLN is eventually employed as vector quantization technique of image compression and thus reducing bit rate and training time.

V. Experimental Results

The codebook design is the primary problem in image compression based on vector quantization. In this paper, the quality of the images reconstructed from the designed codebooks was compared with that from the FSCLN、Wavelet Transform + FSCLN (named by WT+FSCLN) methods. 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. These training vectors built three codebooks of size 64, 128, and 256. The resulting images were evaluated subjectively by the root mean squared error (RMSE) and signal to noise ratio (SNR) that is defined for images of size N×N as

$$RMSE=\left[\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_{ij}-\hat{x}_{ij}\right)^2\right]^{\frac{1}{2}} \tag{14}$$

and

$$SNR=10\log_{10}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}x_{ij}^{2}}{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_{ij}-\hat{x}_{ij}\right)^2} \tag{15}$$

where x_{ij} and $\hat{x}_{ij}$ are the pixel gray levels from the original and reconstructed images. Table 1 shows the SNR and RMSE of the “Girl”, “Lena” and “Couple”, images reconstructed from three codebooks of size 64, 128, and 256 designed by the FSCLN method without wavelet decomposition (named FSCLN) and FSCLN with wavelet decomposition (named by WT+FSCLN). From the experimental results, the reconstructed images obtained from the WT+FSCLN are significantly better than those from the FSCLN algorithm.

In the color compression simulation, the color image information was straightforward separated into RGB planes. Each plane is first decomposed into four subbands in the 1-level wavelet transform. Then the corresponding transformed coefficients are trained using FSCLN to form individual codebooks for each subband. To show the reconstruction performance, the resulting images were evaluated by the average PSNR among three-color planes

$$PSNR_A=\frac{PSNR_R+PSNR_G+PSNR_B}{3} \tag{16}$$

where

$$PSNR = 10\log_{10}\frac{255^2}{\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_{ij}-\hat{x}_{ij}\right)^2},$$

255 is the peak gray level, and $PSNR_R, PSNR_G$, and $PSNR_B$ are the *PSNR* for red, green, and blue planes, respectively. The *PSNRs* of the "Girl", "House", and "couple" images calculated are shown in Table 2, and their reconstructed images using the WT + spread FSCLN each plane are shown in Figure 1. From the simulated results, the proposed WT + Spread FSCLN method is simpler and produce better reconstructed image quality.

VI. Conclusions

In this paper, an unsupervised parallel approach called Frequency-Sensitive Competitive Learning Network (FSCLN) with wavelet decomposition based on vector quantization for color image compression has been presented. Instead of updating the interconnection strengths using the winner-take-all scheme in the conventional competitive learning network, the FSCLN algorithm only modifies output neurons and omits the updating of the interconnection strengths. Experimental results show that the FSCLN is valid for codebook design and the WT+FSCLN method produce promising reconstructed images than those reconstructed by the FSCLN method.

In the color image compression simulation, the presented WT + Spread FSCLN is simpler and produce better reconstructed image quality. It is applicable not only to the RGB color model but also to any other trichromatic model.

References

[1] Y. Linde, A. Buzo, and R. M. Gray, "An Algorithm for Vector Quantizer Design," *IEEE Trans. Commun.*, Vol. COM-28, pp. 85-94, Jan., 1980.

[2] R. M. Gray, "Vector Quantization," *IEEE ASSP Magazine*, Vol.1, pp. 4-29, 1984.

[3] A. Gersho, and R. M. Gray, *Vector Quantization and Signal Compression*, Kluwer Academic Publishers, Norwell, Ma., 1992.

[4] E. Yair, K. Zeger, and A. Gersho, "Competitive Learning and Soft Competition for Vector Quantizer Design," *IEEE Trans. Signal Processing*, Vol. 40, pp. 294-309, 1992.

[5] C. H. Chen, C. Y. Lin, and J. S. Lin, "A Compensated Fuzzy Competitive Learning

Network Applied on Image Compression," *The Fifth Symposium on Computer and Communication Technology,* pp. 1B-11~ 1B -15, 2000.

[6] C. Y. Lin, C. H. Chen, and J. S. Lin, "VQ Codebook Design Using a Genetic Competitive Learning Network," *The 13th IPPR Conference on Computer Vision, Graphics and Image Processing,* pp. 362-369, 2000.

[7] R. Hecht-Nielsen, "Application of Counter-propagation Networks," *Neural Networks*, vol. 1, no. 2, pp. 131-141, 1988.

[8] S. C. Ahalt, A. K. Krishnamurthy, P. Chen, and D. E. Melton, "Vector Quantization Using Frequency-Sensitive Competitive Learning Neural Networks," *Systems Engineering, IEEE International Conference*, pp. 131 –134, 1989.

[9] Moltedo L., Nappi M., Vitulano D. & Vitulano S., "Color image coding combining linear prediction and iterated function systems," *Signal Processing*, 63, 157-162, 1997.

[10] M. Antonini, M. Barlaud, P. Mathieu, and I. Daubechies, "Image Coding Using Wavelet Transform," *IEEE Trans. Image Processing,* Vol.1, pp. 205-220, 1992.

[11] R. A. Devore, B. Jawerth, and B. J. Lucier, "Image Compression through Wavelet Transform Coding," *IEEE Trans. Informat. Theory,* Vol. 38, pp.719-746, 1992.

[12] C. C. Jou, "Fuzzy Clustering Using Fuzzy Competitive Learning Networks," *Neural Networks, IJCNN., International Joint Conference on* , Vol. 2 , pp. 714 –719, 1992.

[13] J. S. Lin, K. S. Cheng, and C. W. Mao, "Segmentation of Multispectral Magnetic Resonance Image Using Penalized Fuzzy Competitive Learning Network," *Computers and Biomedical Research 29*, pp.314-326, 1996.

[14] 戴顯權, "資料壓縮", 松崗, 1998.

Table 1. *SNR* and *RMSE* of the images reconstructed from various compression ratios (*CR*) designed by the FSCLN and WT+FSCLN methods.

Algorithms/CR \ Images		Girl SNR	Girl RMSE	Lena SNR	Lena RMSE	Couple SNR	Couple RMSE
FSCLN	CR=21.33	17.410	9.088	19.282	12.183	14.330	8.364
WT+FSCLN	CR=16.89	19.828	6.881	21.762	9.157	16.764	6.320
FSCLN	CR=18.29	18.460	8.054	20.267	10.876	15.434	7.366
WT+FSCLN	CR=16.89	19.828	6.881	21.762	9.157	16.764	6.320
FSCLN	CR=16	19.328	7.288	21.724	9.197	16.321	6.651
WT+FSCLN	CR=16.89	19.828	6.881	21.762	9.157	16.764	6.320

Table 2. *PSNRs* of color images reconstructed by the WT + Spread FSCLN.

Image/Algorithm \ Plane		R	G	B	Average
Girl	WT + Spread FSCLN	30.5242	30.9564	30.7197	30.7334
House	WT + Spread FSCLN	32.3722	30.5016	30.4187	31.0975
Couple	WT + Spread FSCLN	30.3863	30.4866	30.7614	30.5448

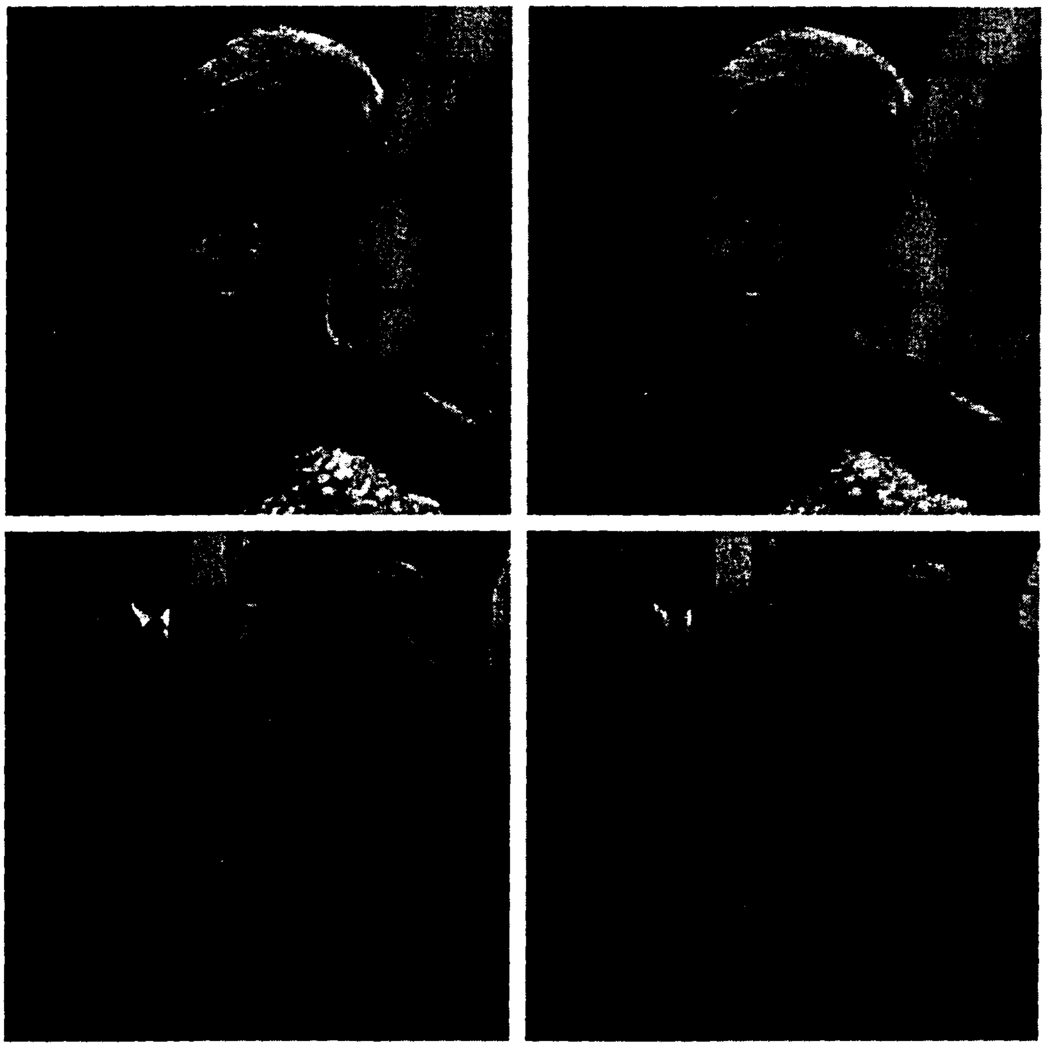

Fig. 1 The "Girl" and "couple" original color images and their reconstructed images using the WT + spread FSCLN each plane