A Neural Approach to Compression of Hyperspectral Remote Sensing Imagery

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Abstract. This paper presents an original research for hyperspectral satellite image compression using a fully neural system with the following processing stages: (1) a Hebbian network performing the principal component selection; (2) a system of "k" circular self-organizing maps for vector quantization of the previously extracted components. The software implementation of the above system has been trained and tested for a hyperspectral image segment of type AVIRIS with 16 bits/pixel/band (b/p/b). One obtains the peak-signal-to-quantization noise ratio of about 50 dB, for a bit rate of 0.07 b/p/b (a compression ratio of 228:1). We also extend the previous model for removal of the spectral redundancy (between the R, G, B channels) of color images as a particular case of multispectral image compression; we consider both the case of color still images and that of color image sequences.

1 Introduction

Over the next decade the volume of image data generated by airborne and spaceborne *remote sensing* missions will increase dramatically due to the commissioning and launching of sensors with high spatial and spectral resolution. The economics of transmission or storage of these *hyperspectral images* dictates that data *compression* is essential. A hyperspectral image comprises a number of bands, each of which represents the intensity of return from an image scene that is received by a sensor at a particular wavelength.

Hyperspectral imagery provides more information than multispectral imagery in the sense that the spectral resolution of the former is much better than that of the latter. While a multispectral image (for example, LANDSAT), generally requires only five to seven bands, a hyperspectral image of type *AVIRIS* (Airborne Visible/Infrared Imaging Spectrometer) [1], [17] simultaneously acquires *224 channels* (bands) of data in the range of 0.4 to 2.45 μm with an average spectral resolution of 10 nm. Channels of AVIRIS image are originally recorded with 12-bit resolution (compared with typically 8 bits for video) but, after radiometric correction, data is stored as 16-bit words. A property of fine-spectral-resolution imagery is interband correlation. The 3-d correlation (two intraband (spatial) correlations as well as the third interband correlation) facilitates substantial reduction of the data required for storing and/or transmitting such imagery.

A well-known method for image compression is to extract the main directions of the input data set; this is equivalent to the computation of the Karhunen-Loeve Transform (KLT) [14]. The corresponding KLT matrix is obtained by computing the eigenvectors of the autocorrelation matrix of the input data. This problem is also called "Principal Component Analysis" PCA).

We have chosen *a neural solution of the PCA* by maximizing the information contained at the outputs of a special neural network called "Hebbian" [5], [14], [16]. If we use a specific training rule called Sanger rule [5], [14], [18], then we can prove that the weight vectors do not depend on the initial conditions and they will always converge to the eigenvectors of the autocorrelation matrix of the input data. Since then, *the Hebbian net may be considered as a neural equivalent of the KLT.*

Another common image compression method is *vector quantization*, which can achieve high compression ratios [9]. A vector quantizer makes use of the fact that a large number of possible blocks in an image look similar. These blocks are mapped to a single block (called *prototype* of the corresponding class), which is given a code that has fewer bits than the actual block representation. The image compression problem then becomes the task of finding the block in the codebook, which most closely represents an original block (namely, finding the *nearest prototype*).

Some advanced techniques for *vector quantization* belong to the field of *computational intelligence* using *neural* models. *Neural vector quantization* of images [11], [12], [13], [15] is based especially on the Kohonen Self-Organizing Map (SOM) [7]. Neighboring neurons in the above-unsupervised neural network develop adaptively into specific detectors of different vector patterns. The neurons become specifically tuned to various classes of patterns through a competitive, unsupervised or self-organizing learning. Only one cell (neuron) or group of cells at a time gives the active response to the current input. The spatial location of a cell in the network (given by its co-ordinates) corresponds to a particular input vector pattern.

First contribution of the present paper is the design, software implementation and evaluation of a fully neural model for compression of hyperspectral satellite imagery (instead of the conventional (non-neural) methods used in [1]). Our model consists of a Hebbian network (for principal component selection, that extracts the 3-d correlation of the hyperspectral image data) cascaded by a set of Kohonen network (for neural vector quantization). *The second contribution of the paper is to extend the present model based on interband correlation by considering a color image as a multispectral picture corresponding to the three R, G, B principal components*. For compression of color still images, the scheme remains the same as for hyperspectral satellite images, but the number of bands becomes three. For representation of color image sequences, the model includes a first processing stage consisting of a 4-dimensional orthogonal transform (instead of the 3-d transform used for hyperspectral imagery) for extraction of the principal component of the input color image sequence followed by a second processing stage of *neural* vector quantization. The experimental compression results are given both for the principal model (compression of hyperspectral satellite imagery) as well as for the special application (compression of color images).

2 A Fully Neural Model for Compression of Hyperspectral Imagery

2.1 Model Description

The proposed model (Fig. 1) contains the following processing cascade:

(a) The Hebbian network for *extraction of the principal components*;

(b) A set of self-organizing neural networks (Kohonen) for *vector quantization* of the principal components.

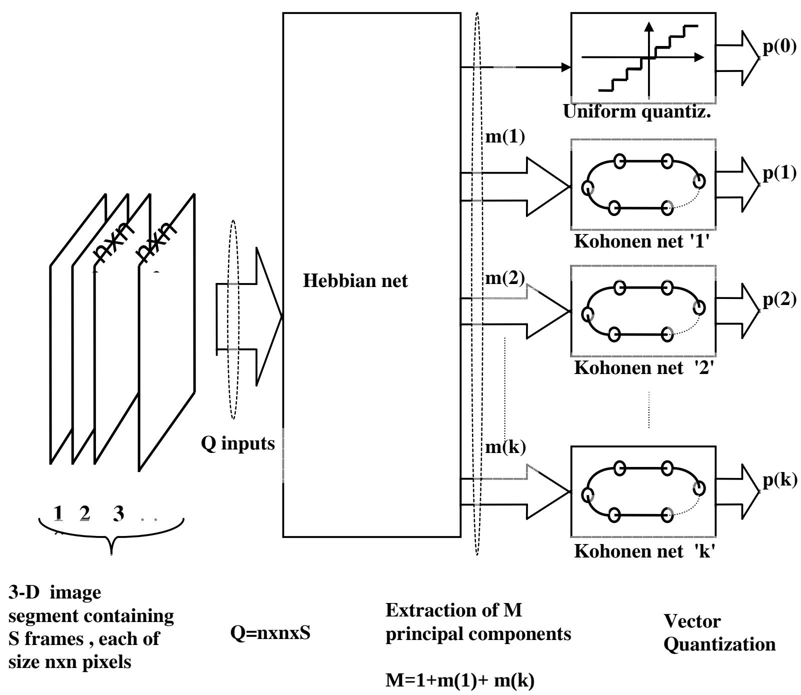


Fig. 1. Architecture of the neural system for compression of hyperspectral imagery.

(a) *The Hebbian network* processes the 3-d elementary blocks of "n x n x S" pixels of the input hyperspectral sequence (where "n x n" is the elementary analysis square in each "N x N" pixel band, and S is the number of bands. This network is a neural replica of the optimum 3-d Karhunen-Loeve transform.

To improve the convergence, we have chosen the initial weights of the network to be given by the elements of the matrix defining the 3-d Discrete Cosine Transform (3-d DCT). The network has Q=n x n x S inputs, corresponding to the above-mentioned 3-d multispectral segment and M outputs, corresponding to the principal components. The neural variant has the advantage (over the non-neural one=KLT) of deducing the optimum transformation by a simple and iterative technique instead of requiring a significant computational effort for evaluating the autocorrelation matrix, the eigenvalues and eigenvectors!

(b) *The system of "k" circular self-organizing map*s performs vector quantization of the M-1 (AC) principal components, given by the Hebbian network. These components are grouped into "k" subsets, so that m (1) + m (2)+…+m (k)= M-1, where m (h) is the number of inputs of the self-organizing map of index "h"; each network has 2exp[p (h)] neurons (outputs), where p (h) is the number of bits for encoding the segment "h" of the principal component set. First component is uniformly quantized with p (0) bits. Since then, the bit rate provided by the neural compression system is R = p (0)+p (1)+…+p (k)]/(n x n x S) bits/pixel/band (b/p/b). The radius of the neighborhood of each neuron decreases with the iteration. The *circular* architecture of the network implies a perfect symmetry.

2.2 Experimental Results for Compression of Hyperspectral Imagery

We have used hyperspectral images of the type AVIRIS (Airborne Visible/Infrared Imaging Spectrometer). The images are selected from a hypercube containing 128 spectral bands, each band with 128 **x** 128 pixels. The images are represented with a radiometric resolution of 16 bits/pixel/band and correspond to an urban area.

2.2.1 Training

a. Selection of the principal components (Hebbian Network)

- We have used S=8 spectral bands (avir_1.raw,….., avir_8.raw)
- The size of each band: N x N= 128 x 128 pixels
- Resolution: 16 bits/pixel
- The input multispectral image is segmented into 3-D blocks of 8 x 8 x 8 (namely, n=S=8)
- Number of inputs of the Hebbian network: n x n x S=512
- Number of outputs (selected components): M= 20

The training of the Hebbian network may be evaluated in Table 1.

b. Quantization of the Principal Components (Neural Self-Organizing System)

- The DC coefficient is scalar quantized with p (0)=9 bits.
- The set of M-1 = 19 AC coefficients are vectorially quantized by segmenting the set into k = 3 subsets of sizes: m (1)=7; m (2)=6; m (3)=6.

• Each of the three neural networks has a circular architecture with 512 neurons (it implies that a corresponding prototype is encoded with p (1)=p (2)=p (3)= 9 bits).
• The resulted bit rate is R= (9+27)/512= 0.07 bits/pixel/band (b/p/b), corresponding to the compression factor of F=16/0.07=228:1.
• The objective quality of the reconstructed bands of the hyperspectral training image after processing by the Hebbian network, *with* and *without* neural quantization may be evaluated from the Table 2.

Table 1. Peak signal-to-quantization noise ratios during the refinement of the Hebbian network for the hyperspectral image AVIRIS (8 bands: avir_1.raw, avir_2.raw,…,avir_8.raw); number of retained coefficients: M=20 (t= index of epoch)

t (epoch)	0	1	2	3	4	Frozen after t=4
(PSNR) dB (Global)	49.56	49.65	49.77	49.84	49.87	49.87
(PSNR) dB (Band1)	48.41	48.79	49.53	50.10	50.52	50.73
(PSNR) dB (Band 2)	51.37	51.35	51.31	51.21	51.07	51.01
(PSNR) dB (Band 3)	51.06	51.00	50.87	50.75	50.65	50.59
(PSNR) dB (Band 4)	48.72	48.80	48.94	49.05	49.16	49.20
(PSNR) dB (Band 5)	50.04	50.11	50.23	50.33	50.41	50.45
PSNR) dB (Band 6)	50.76	50.78	50.84	50.86	50.86	50.87
(PSNR) dB (Band 7)	51.05	51.21	51.43	51.53	51.55	51.54
(PSNR) dB (Band 8)	47.11	47.10	47.00	46.91	46.83	46.76

Table 2. Peak signal-to-quantization noise ratios of the hyperspectral *trainin*g sequence AVIRIS (8 bands: avir_1.raw,…,avir_8.raw) processed firstly by the Hebbian network (after freezing the weights obtained during 4 epochs of training and retaining M=20 components) and then reconstructed *without* or *with* neural quantization

	Global	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7	Band 8
(PSNR) dB Reconstruc-tion **without** quantization	49.87	50.73	51.01	50.59	49.20	50.45	50.87	51.54	46.76
(PSNR) dB Reconstruc-tion **with.** quantization	49.69	50.53	50.79	50.39	49.05	50.25	50.65	51.28	46.64

•We can remark a high fidelity of the quantization (the global signal-to-quantization noise ratio decreases only from 49.87 dB to 49.69 dB as effect of quantization!).

• In Fig. 2 (a, b, c), we can subjectively evaluate the quality of the reconstructed image corresponding to Table 2 (band 3 of the considered training image). Visually, we cannot remark any difference between the input and the reconstructed image.

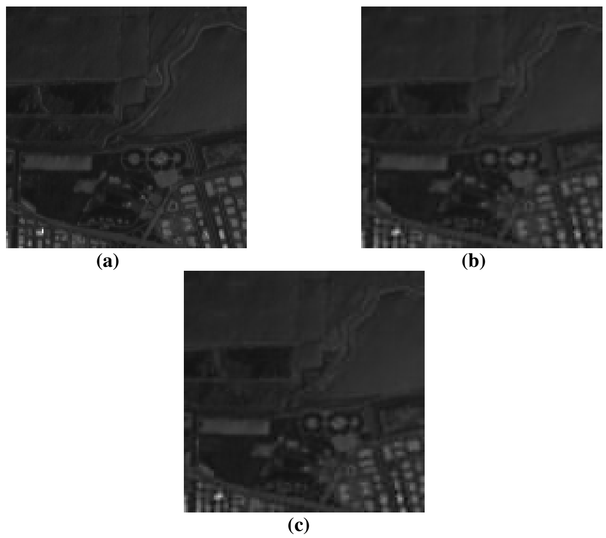


Fig. 2. **(a)** Original band 3 (avir_3.raw). **(b)** Band 3 reconstructed after Hebbian selection of the principal components without quantization (PSNR=50.59 dB). **(c)** Band 3 reconstructed after Hebbian selection of the principal components and vector quantization with a system of three self-organizing neural networks (PSNR=50.39 dB, R= 0.07 b/p/b; compression ratio=228:1).

2.2.2 Testing

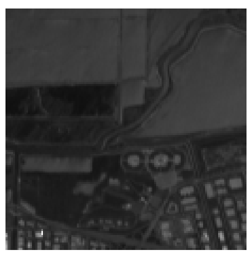
• We have used the set of eight bands of the hyperspectral image (avir_9.raw,…,avir_16.raw), different from those used for training, but corresponding to the same urban area.

• The parameters of the input sequence, those of the Hebbian network, as well as those of the Kohonen system are the same as for the training phase.

• In Table 3, we can evaluate the objective quality of the reconstructed picture (peak signal-to-quantization-noise ratio =PSNR) for the hyperspectral test image, while in Fig. 3 (a, b, c) we can visually evaluate the reconstructed test picture (band 10). *The signal-to-noise ratio (**about 50 dB!**) and the high compression ratio (of **228:1**) combine the high quality of reconstruction with an important coding efficiency.*

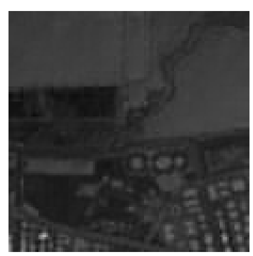
Table 3. Peak signal-to-quantization noise ratios of the hyperspectral *test* sequence AVIRIS (8 bands: avir_9.raw,…,avir_16.raw) processed firstly by the Hebbian network, and then reconstructed *without* or *with* neural vector quantization (after freezing the weights obtained during 4 epochs of training and retaining M=20 components). The neural system has been trained on the multispectral sequence of 8 bands: avir_1.raw,…,avir_8.raw.

	Global	Band 9	Band 10	Band 11	Band 12	Band 13	Band 14	Band 15	Band 16
(PSNR) dB Reconstruction **without** quantization	**49.10**	46.16	50.46	50.15	48.62	49.57	50.73	50.33	48.83
(PSNR) dB Reconstruction **with** quantization	**47.95**	45.40	48.87	48.83	47.69	48.41	49.18	48.60	47.93



(a)

(b)



(c)

Fig. 3. (a) Band 10 original (avir_10.raw; 128 x 128 pixels). **(b)** Band 10 reconstructed after Hebbian selection of the principal components without quantization (PSNR=50.46 dB). **(c)** Band 10 reconstructed after Hebbian selection of the principal components and vector quantization with a system of 3 self-organizing neural networks (PSNR=48.87dB, R= 0.07 b/p/b; compression ratio=228:1). The neural system (Hebbian + Kohonen) has been trained on the multispectral sequence of 8 bands: avir_1.raw,…, avir_8.raw.

3 Removal of the Spectral Redundancy of Color Images as a Particular Case of Multispectral Image Compression

3.1 Compression of Still Color Images

We further extend the present model based on interband correlation by considering a color image as a multispectral picture corresponding to the three R, G, B component images! For compression of color still images, the scheme remains the same as for hyperspectral satellite images, but the number of bands becomes 3. Thus, *we build an original model for color image representation,* by considering in the same 3-d orthogonal transformation not only the 2-d spatial correlation ***but also the spectral correlation between the R, G, and B components***! One can approximate the Hebbian network by a suboptimum 3-d orthogonal transform like 3-d Discrete Cosine Transform (3-d DCT) with a small reduction of data compression performances but with a significant increasing of the computation speed.

Experimental Results

We have trained and tested this special application for the color picture "Girl" of 512 x 512 pixels, represented in true-color bmp (24 bits/pixel).

General parameters

- The 3-d segment has the sizes: $n_1 = n_2 = 8$, $S = 3$, corresponding to the hyper-rectangle of 8 x 8 x 3.
- Number of retained coefficients (principal components) after 3-d DCT processing: M=25
- The first 3-d DCT coefficient (0,0,0) has been scalar quantized with p (0) = 8 bits.

Parameters of the neural system

- The set of M-1 = 24 AC coefficients are vectorially quantized by segmenting the set into k= 3 subsets of sizes: m (1)= m (2)= m (3)=8, each subset containing the inputs of a corresponding circular self-organizing map for vector quantization.
- Size of each ring network: 256 x 1 (p (1) = …. =p (3)= 8 bits)
- The resulted bit rate is R= (8+24)/(8 x 8 x 3) = 0.167 bits/pixel/channel (b/p/c), or, for other representation is R= (8+24)/(8 x 8)=0.5 bits/true-color pixel. It corresponds to the compression factor of F=24/0.5=48:1.

Table 4. Signal-to-quantization noise ratios for each color channel of the reconstructed color image "Girl" after 3-d DCT and neural vector quantization

(PSNR) red [dB]	(PSNR) green [dB]	(PSNR) blue [dB]
25.02	22.37	26.60

The *objective quality of the reconstructed "Girl" is given in Table 4 and the subjective* quality of the reconstructed color image after compression may be evaluated from Fig. 4.

(a)

(b)

Fig. 4. (a) Original "Girl". **(b)** Reconstruction of the "Girl" after 3-d DCT and neural quantization (compression ratio R=48:1).

3.2 Compression of Color Image Sequences

We extend for color image sequences the previous model of compression of hyperspectral images. Instead of separately processing the color image sequences (for each of the fundamental colors R, G, B), we have chosen a global processing for redundancy removal taking into account in the same processing stage the 4-d correlation of the color image sequences: two dimensions of spatial correlation, one dimension for temporal correlation *and also one dimension for spectral correlation (corresponding to the R, G, B bands!). We choose a 4-dimensional orthogonal transform for color sequence representation,* instead of the well-known 3-d transform or hybrid coding (2-d transforms combined with prediction) for each color components. Thus, we consider in the same orthogonal transformation not only the spatial correlation and the temporal one*, but also the spectral correlation between the R, G, B channels. For example, we have chosen* a 4-dimensional Discrete Cosine Transform (4-d DCT), that is an approximation of the KLT (Hebbian net) that reduces the computational complexity. The 4-d DCT coefficients are given by the relation

$$C(k_1,k_2,k_3,k_4)=\frac{u(k_1)\cdot u(k_2)\cdot u(k_3)\cdot u(k_4)}{\sqrt{N_1N_2N_3N_4}}\cdot$$

$$\left(\sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1}\sum_{n_3=0}^{N_3-1}\sum_{n_4=0}^{N_4-1} x(n_1,n_2,n_3,n_4)\cos\frac{\pi(2n_1+1)k_1}{2N_1}\cos\frac{\pi(2n_2+1)k_2}{2N_2}\cos\frac{\pi(2n_3+1)k_3}{2N_3}\cos\frac{\pi(2n_4+1)k_4}{2N_4}\right)$$

where $u(k_i)=\begin{cases}1, & k_i=0\\ \sqrt{2}, & k_i=1,\ldots,N_i-1\end{cases}$

$i\in 1,2,3,4$, n_i and k_i belong respectively to the sets $\{0,\ldots,N_1-1\}$, $\{0,\ldots,N_2-1\}$, $\{0,\ldots,N_3-1\}$ and $\{0,\ldots,N_4-1\}$. Here, $N_1 = N_2 = n$ (elementary analysis square); N_3 is equal to S=frame number; $N_4 = 3$ (number of channels). In the previous relation, we consider that a color image sequence segment expressed in the (R, G, B) format are represented by the corresponding 4-dimensional matrix x (i, j, k, h), for $i = 0,\ldots, N_1-1$, $j = 0,\ldots,N_2-1$, $k = 0,\ldots,N_3-1$ and $h = 0,\ldots,N_4-1$. The M retained 4-d DCT coefficients corresponding to the principal components of the input color image sequence segment are grouped in several sets (vectors) and each such a vector is applied to a corresponding *neural quantizer* .

Processing stages of the proposed model:

(a) a 4-d orthogonal transform of each input 4-d matrix of "N_1 x N_2 x N_3 x N_4" fundamental color pixels into a set of M selected components in the frequency domain (where N_1 x N_2 are the sizes of the square analysis segment of a certain frame, N_3 is the number of frames considered to be redundant, and a color pixel corresponds to N_4 =3 monochrome pixels, one for each of the fundamental colors R, G, B).

(b) a neural vector quantization system, consisting of "k" vector quantizers of the M-1 selected components (the AC ones) obtained as a result of the previous processing stage, where the selected components are grouped into "k" subsets

Remarks:

- All "k" neural vector quantizers are trained using one or several image sequences.
- After training, we perform the processing of an input sequence according to the previous mentioned stages (a) and (b).

(a)

(b)

Fig. 5. (a) Original first frame of the color sequence "Miss America". **(b)** Reconstruction of the first frame of the color sequence "Miss America" (having 8 frames) using the proposed neural model (trained on the same sequence) (compression ratio R=150:1).

Experimental Results

We have designed and implemented the software of the **neural** system shown in Fig. 1, where instead of the Hebbian network, we have used a 4-d DCT. For experimenting the corresponding system, we have used two image sequences: "Miss America" (misa) and "Salesman"; each experimental sequence had a length of maximum 64 frames of 256 x 256 pixels /frame with 24 bits/true-color pixel.

General parameters

• Number of retained coefficients (principal components): M=270

• The first 4-d DCT coefficient (0,0,0,0) has been scalar quantized with p (0) = 10 bits.

Parameters of the neural system

We have used a system of k=9 circular self-organizing maps (Kohonen networks). Each network has a number of 2exp [p (h)] neurons (outputs), where p (h) is the number of bits to encode the group ("h") of m (h) principal components. The neural system has the following parameters:

• *First six networks:*

♦ number of inputs: m (1) = …=m (6)=36;

♦ size of the ring networks: 256 x 1 (p (1) = …. =p (6)= 8 bits)

• *Seventh and eight networks:*

♦ number of inputs: m (7) = m (8)=37

♦ size of the ring networks: 256 x 1; (p (7) = p (8)=8 bits)

• *Ninth network*

♦ number of inputs: m (9) = 39

♦ size of the ring network: 256 x 1 (p (9) = 8 bits).

• Resulted bit rate is BR=0.16 bits/true-color pixel (compression ratio R= 150:1)

• The peak signal-to-quantization noise ratios of the reconstructed first frame of the sequence "Miss America" (for the main bands R, G, B) are given in Table 5, while the *subjective* quality of the reconstructed color frame after compression may be evaluated in Fig. 5.

Table 5. Signal-to-quantization noise ratios for each color channel of the reconstructed first frame of the color sequence „Miss America".

(PSNR) red [dB]	(PSNR) green [dB]	(PSNR) blue [dB]
33.54	34.95	33.14

4 Concluding Remarks

1. This paper *presents a fully neural model for compression of hyperspectral satellite imagery* consisting of a Hebbian network (for principal component selection, that extracts the 3-D correlation of the hyperspectral image data) cascaded with a set of ring Self-Organizing Maps (for neural vector quantization of the previously extracted components).

2. By the proposed neural model, we point out the feasibility of applying an exciting technique of computational intelligence for compression of satellite imagery, instead of the conventional techniques.

3. If we compare the Hebbian network with the KLT, the neural variant has a significant advantage in reducing the computational effort, avoiding the necessity of deducing the autocorrelation matrix, its eigenvalues and eigenvectors and so on. The neural vector quantization proves also to be competitive with the classical (non-neural) vector quantization for the image compression task.

4. We give the experimental results of the software implementation of the previous model for compression of the hyperspectrral images AVIRIS. One obtains very good results: the peak-signal-to-quantization-noise-ratio of about 50 dB for each band, for a bit rate of 0.07 b/p/b (a compression ratio of 228:1). *This means a high quality of image reconstruction combined with a significant coding efficiency.*

5. As a special application, we extend the present model based on interband correlation by considering a color image as a multispectral picture corresponding to the three R, G, B channels. For compression of color still images, the scheme remains the same as for hyperspectral satellite images, but the number of bands becomes 3, corresponding to the R, G, B channels. Thus, *we obtained an original model for color image representation,* by considering in the same 3-d orthogonal transformation not only the 2-d spatial correlation *but also the spectral correlation between the R, G, B components*! To increase the computation speed we replace the Hebbian network by the 3-d DCT.

6. By extending the initial scheme to *the representation of color image sequences*, *we build a new model that includes a 4-dimensional orthogonal transform as a first processing stage* (instead of the 3-d transform for hyperspectral imagery) for extraction of the principal components. Thus, we consider in the same 4-d orthogonal transformation the redundancy removal corresponding to the following four correlation dimensions: the 2-d spatial correlation (the first two dimensions), the temporal one (the third dimension), and the spectral correlation between the R, G, B bands (the fourth dimension)! We have applied this 4-d orthogonal representation model for the particular case of the 4-d DCT, instead of the Hebbian net, to reduce the computational effort. The second processing stage (*neural* vector quantization) remains the same as for compression of hyperspectral images.

7. The very good experimental compression results are obtained both for color still images (compression ratio of 48:1) and also for color image sequences (compression ratio of 150:1).

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