論 文

Progressive Image Transmission using LOT / CVQ with HVS Weighting

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HVS가중치를 갖는 LOT / CVQ를 이용한 점진적 영상전송

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ABSTRACT

A progressive image transmission (PIT) scheme based on the classified transform vector quantization (CVQ) technique using the lapped orthogonal transform (LOT) and human visual system (HVS) weighting is proposed in this paper. Conventional block transform coding of images using DCT produces in general undesirable block-artifacts at low bit rates. In this paper, image blocks are transformed using the LOT and classified into four classes based on their structural properties and further divided adaptively into subvectors depending on the LOT coefficient statistics with HVS weighting to improve the reconstructed image quality by adaptive bit allocation. The subvectors are vector quantized and transmitted progressively. Coding tests using computer simulations show that the LOT / CVQ based PIT of images is an effective coding scheme. The results are also compared with those obtained using PIT / DCTVQ. The LOT / CVQ based PIT reduces the block-artifacts significantly.

要 約

LOT(Lapped Orthogonal Transform)와 HVS(Human Visual System) 가중치를 이용하여 분류벡타양자화기에 근거한 점진적 영상부호화 방법을 제안하였다. DCT변환을 이용한 기존의 블럭변환 영상부호화는 낮은 전송율에서 블럭화 현상이 심하게 나타난다. 본 논문에서는 영상블럭을 LOT로 변환하고 그 블럭들의 구조적 특성에 따라 네 부류로 분류한 다음 적응비트배정으로 재생 영상화질을 개선하기위해 HVS가중치를 갖는 LOT계수특성에 의해 서브벡타들로 나눈다. 이 서브벡타들을 벡타양자화하여 점진적으로 전송한다. 컴퓨터 시뮬레이션을 통한 부호화시험을 하여 점진적 전송에 의한 LOT / CVQ가 효율적인 전송임을 보이고 PIT / DCTVQ를 이용한 결과와 비교하였다.

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論文番號：93－69

I. Introduction

An effective image data compression scheme to reduce the bit rate for transmission or data storage while maintaining, an acceptable image quality is essential for applications such as video teleconferencing, HDTV transmission, fascimile transmission etc. Numerous bandwidth compression techniques have been developed, such as differential pulse code modulation (DPCM), transform coding (TC)[1], hybrid coding, and adaptive versions of these techniques with new image processing methods[2]. In these methods, block TC is used to convert statistically dependent or correlated pels into independent or uncorrelated coefficients. Among several block transform methods, it is known that the discrete cosine transform (DCT)[3] approaches the statistically optimal transform, Karhunen-Loueve transform (KLT), for highly correlated images. Vector quantization of coefficients [4]-[6] helps reach the rate-distortion bound of the source. Various techniques which apply VQ to DCT coefficients of still frame images or interframe prediction errors of motion video have been investigated. These techniques, however, can result in block artifacts at low bit rates. Several techniques have been developed to reduce or eliminate these artifacts. One effective technique is to apply the lapped orthogonal transform (LOT)[7]-[9] whose basis functions extend beyond the traditional block boundaries. Besides reducing the block structure, LOT also has some interesting filtering properties. Also LOT is a real transform having a fast algorithm[8],[9]. Being a separable transform, extension to multiple dimensions is straight forward. In this paper, an image compression scheme for PIT using LOT/VQ is proposed taking advantages of these properties. Also classification [10]-[12] in the LOT domain is introduced to adapt to the directional structural properties within the blocks in the spatial domain. Each of the classified 8×8 block in the LOT domain is adaptively partitioned into a number of subvectors of smaller dimensions according to their variances and HVS [13],[14] weighting. The subvectors for each class are progressively transmitted in several stages until the final required image quality is achieved. This technique [15] allows an approximate image to be built quickly and the details transmitted progressively through several passes in interactive communications over low-bandwidth channels. The image quality at each stage using LOT/CVQ is compared with that of DCT/CVQ based on subjective and objective criteria. This is useful in interactive visual communications, in which a viewer can decide to build up an image quality for further analysis based on a crude version or pass on to another image from large data base stored in compressed form.

II. Implementation of the LOT

The LOT has and orthogonal set of basis functions which extend beyound the block boundaries to overlap parts of the adjacent blocks. Cassereau et al. [7] derived a set of basis functions by a recursive optimization procedure, but it suffered from error propagation during the optimization and also had no fast algorithm. Recently Malvar [8],[9] developed an optimal set of basis functions which can be implemented as a fast algorithm. LOT matrix is obtained by a series of rotations to overlap the block boundaries starting from a DCT matrix. Hence the key to a fast algorithm for the LOT is the approximation of the rotation matrix by a product of a few simple factor, called butterfly stages. Consider M blocks of length N; if $\mathbf{x}_0$ is the input vector of length MN, then the transform coefficient vector $\mathbf{y}_0$ is given by

$$\mathbf{y}_0 = \mathbf{T}'\mathbf{x}_0 \tag{1}$$

where $\mathbf{T}'$ is the transpose of the MN×MN block diagonal matrix, $\mathbf{T}$. The LOT matrix $\mathbf{T}$ is represented by

$$\mathbf{T}=\begin{bmatrix} \mathbf{P}_1 & & & & 0 \\ & \mathbf{P}_0 & & & \\ & & \ddots & & \\ & & & \mathbf{P}_0 & \\ 0 & & & & \mathbf{P}_2 \end{bmatrix} \qquad (2)$$

where $\mathbf{P}_0$ is an $L \times N$ matrix that contains the LOT basis functions for each block. The key point to develop the fast algorithm is to choose a feasible LOT matrix $\mathbf{P}$ that is not necessarily optimal, and obtain an orthogonal matrix $\mathbf{Z}$ which can be approximated by a product of butterflies such that

$$\mathbf{P}_0 = \mathbf{P} \cdot \mathbf{Z} \qquad (3)$$

A feasible matrix is obtained using the DCT basis functions as

$$\mathbf{P} = \frac{1}{2}\begin{bmatrix} \mathbf{D}_e - \mathbf{D}_o & \mathbf{D}_e - \mathbf{D}_o \\ \mathbf{J}(\mathbf{D}_e - \mathbf{D}_o) & -\mathbf{J}(\mathbf{D}_e - \mathbf{D}_o) \end{bmatrix} \qquad (4)$$

where $\mathbf{D}_e$ and $\mathbf{D}_o$ are $N \times N/2$ matrices with the even and odd DCT functions respectively and $\mathbf{J}$ is the $N \times N$ counter identity matrix. The orthogonal matrix, $\mathbf{Z}$, in (3) can be approximated as follows for data with high correlation coefficient.

$$Z = \begin{bmatrix} I & 0 \\ 0 & \tilde{Z} \end{bmatrix} \qquad (5)$$

Then the $N/2 \times N/2$ matrix $\tilde{Z}$ can be approximately factored into a series of plane rotations as

$$\tilde{Z} = T_1 T_2 \cdots T_{\frac{N}{2}-1} \qquad (6)$$

Each plane rotation is defined as

$$T_i = \begin{bmatrix} I_{i-1} & 0 & 0 \\ 0 & \begin{bmatrix} \cos\theta_i & \sin\theta_i \\ -\sin\theta_i & \cos\theta_i \end{bmatrix} & 0 \\ 0 & 0 & I_{(N/2)-(i+1)} \end{bmatrix} \qquad (7)$$

where θ_i is the rotation angle to be determined to maximize the transform coding gain. For an $N=8$, $L=16$ LOT, the rotation angles are given by $\theta_1 = \theta_3 = 0.13$, $\theta_2 = 0.16$. The LOT of the first and last blocks, $\mathbf{P}_1$, $\mathbf{P}_2$ in (2) are obtained by reflecting the data at the segment boundaries.

Ⅲ. PIT using LOT/ CVQ

1. Classified VQ based on LOT(LOT/ CVQ)

A classificaion scheme is used in the LOT domain to classify blocks into perceptually distinct classes according to the directional activity in them. Blocks from different activity classes are then adaptively partitioned into a number of subvectors of small dimensions according to their variance distribution and human visual sensitivity for low frequency components. The coding scheme is depticted in Fig. 1.

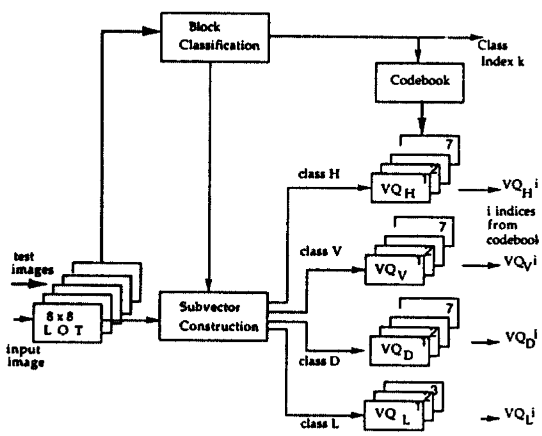


Fig. 1. The LOT /CVQ coding scheme

Although several activity measures have been proposed for transform block classification[16], the relationship between directional activity in the spatial domain to that in the transform domain is exploited simply in our scheme. The LOT blocks are classified into 4 classes[11]: one low activity class and 3 activity classes corresponding to the edge orientation in the spatial domain-horizontal, vertical and diagonal. The blocks are classified based on three activity indices calculated using the coefficients in the regions shown in Fig. 2. If the indices are below a certain threshold, the block is classified as a low activity block.

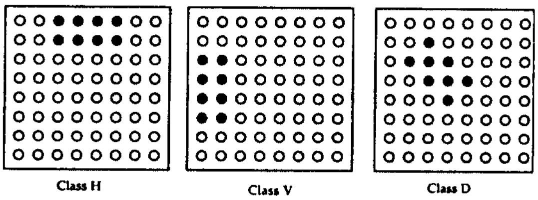


Fig. 2. Regions for three activity classification of 8×8 LOT blocks

Since the variances of the LOT coefficients vary widely, it would be inefficient to use the same quantizer for all the coefficients. Hence, for each class of LOT coefficient block, the 8×8 block is adaptively partitioned into a number of subvectors of small dimensions, taking the complexity of VQ computation, according to their variances. In our scheme, the blocks belonging to the high activity classes are partitioned into seven subvectors and those of the low activity class into three subvectors based on the variance distributions. Variance distributions for the four classes and one possible corresponding subvector construction based on four test images are shown in Fig. 3 and Fig. 4 respectively.

Class H -

213867	22890	7299	3155	1522	469	659	185
17071	3259	3497	1213	1232	311	635	123
2248	571	666	343	380	171	161	81
1133	361	366	204	198	160	108	50
848	156	222	99	119	67	71	35
886	105	173	73	97	42	61	31
540	64	109	47	66	37	41	20
557	65	113	40	60	25	36	15

Class V -

158524	4277	1733	565	634	147	383	69
21787	2983	1587	423	603	120	365	67
7966	2068	902	331	291	114	151	51
4711	1494	627	296	193	109	86	48
2434	1036	579	247	166	85	74	45
1824	719	425	230	141	82	72	41
1123	458	349	179	134	79	72	37
1318	381	303	152	122	62	51	31

Class D -

160966	9269	1072	857	384	263	163	129
9101	6699	2926	753	416	238	137	123
1147	3104	2982	1471	584	308	149	120
932	924	1660	1176	568	301	156	101
428	546	661	744	382	220	114	81
347	319	375	353	258	178	115	85
228	245	244	203	170	132	86	67
203	215	192	153	130	124	80	56

Class L -

291441	1079	117	101	33	33	16	16
563	250	82	53	29	19	13	11
84	77	56	37	26	19	12	10
81	53	43	31	23	63	19	11
45	37	30	23	18	18	11	9
36	26	24	18	16	17	13	10
26	21	18	14	15	19	15	9
23	18	14	12	11	11	8	6

Fig. 3. Variance distributions of four classes based on four combined test images in the LOT domain.

1	2	3	3	4	5	5	7
2	3	3	4	4	6	5	7
3	5	5	6	6	7	7	
4	6	6	6	6	7	7	
4	7	6	7	7			
4	7	7					
5							
5							

Class H

1	3	4	6	6		7	
2	4	4	7	6		7	
3	4	5	7	7			
3	5	6	7				
4	5	6					
4	6	7					
5	7	7					
5	7	7					

Class V

1	2	4	4	5	7		
2	2	3	4	5	7		
4	3	3	4	5	6		
4	4	4	4	5	6		
5	5	5	5	6	7		
6	6	6	6	7			
7	7	7	7				

Class D

1	2	3	3				
2	2	3					
3	3						
3							

Class L

Fig. 4. Subvector configurations in each class based on the variance distributions shown in Fig.3.

In Fig. 4, LOT coefficients with the same digit belong to the same subvector and blank squares imply that the corresponding LOT coefficients are discarded. As shown in Figs. 3 and 4, the selection of LOT coefficients to construct subvectors is not clear especially among high frequency components. Hence an improvement in the reconstructed image quality on subjective criteria can be expected by partitioning the subvectors adaptively based on the significance of transform coefficients to human visual system (HVS). Several schemes for the modulation transfer function (MTF) of the HVS model have been proposed [13]. Recently Chitprasert and Rao [14] proposed a MTF for use with DCT that yields good results for PIT. The MTF for the one-dimensional case, which has a peak at f=3.75 cycles per degree (cpd), is given by

$$H(f) = 1.2356(0.1+0.25f)\exp(-0.25f) \tag{8}$$

The 2-D weighting function H(k, m) is mapped to H(f) as follows

$$H(k, m) = \frac{H(f)}{C^2(k)\,C^2(m)}, \quad k, m = 0, 1, \cdots, N-1 \tag{9}$$

where

$$C(k) = C(m) = \frac{1}{\sqrt{2}} \quad \text{for } k=0$$
$$= 1 \quad \text{for } k = 1, 2, \cdots, N-1 \tag{10}$$

Also, for an isotropic model of the MTF, f is given by

$$f = \frac{\sqrt{k^2+m^2}}{2N} f_s \quad \text{cpd} \tag{11}$$

where f_s is sampling density which depends upon the viewing distance. For a sampling density, f_s, of 64 pels/degree, the weighting function is shown in Fig. 6.

0.494	1.000	0.702	0.381	0.186	0.085	0.037	0.016
1.000	0.455	0.308	0.171	0.085	0.039	0.017	0.008
0.702	0.308	0.214	0.124	0.065	0.031	0.014	0.006
0.381	0.171	0.124	0.077	0.042	0.022	0.010	0.005
0.186	0.085	0.065	0.042	0.025	0.013	0.007	0.003
0.085	0.039	0.031	0.022	0.013	0.008	0.004	0.002
0.037	0.017	0.014	0.010	0.007	0.004	0.002	0.001
0.016	0.008	0.006	0.005	0.003	0.002	0.001	0.001

Fig. 6. The HVS weighting function H(k, m)

The new variance distribution after HVS weighting and the corresponding subvector construction are shown in Fig. 7.

Class H -

SV	1	2	3	4	5	6	7	
1	52241	22891	3600	459.0	52.42	3.388	0.921	0.047
2	17072	674.3	332.8	35.33	8.803	0.478	0.193	0.007
3	1109	54.35	30.48	5.319	1.583	0.165	0.033	0.003
	164.9	10.53	5.668	1.217	0.358	0.074	0.011	0.001
5	29.20	1.188	0.927	0.179	0.074	0.012	0.003	0.000
6	6.394	0.163	0.168	0.034	0.017	0.002	0.001	0.000
7	0.755	0.020	0.022	0.005	0.003	0.001	0.000	0.000
	0.134	0.004	0.004	0.004	0.001	0.000	0.000	0.000

Class V -

SV	1	3	4	5	6	7		
1	38723	4277	854.8	82.28	21.85	1.061	0.536	0.018
2	21787	617.3	151.1	12.32	4.307	0.185	0.111	0.004
3	3929	196.8	41.30	5.125	1.214	0.110	0.031	0.002
4	685.3	43.51	9.716	1.763	0.348	0.051	0.009	0.001
5	83.83	7.404	2.414	0.446	0.103	0.015	0.003	0.000
6	13.16	1.106	0.410	0.106	0.025	0.005	0.001	0.000
7	1.568	0.139	0.071	0.019	0.006	0.001	0.000	0.000
	0.337	0.022	0.012	0.003	0.001	0.000	0.000	0.000

Class D -

SV	1	2	3	4	5	6	7	
1	39319	9268	528.6	124.7	13.23	1.898	0.228	0.033
2	9101	1386	278.5	21.93	2.971	0.366	0.042	0.007
3	565.7	295.5	136.4	22.76	2.434	0.297	0.030	0.005
4	135.7	26.91	25.70	6.992	1.026	0.139	0.017	0.002
5	14.76	3.905	2.754	1.341	0.236	0.039	0.005	0.001
6	2.500	0.490	0.362	0.163	0.046	0.010	0.002	0.000
7	0.318	0.074	0.049	0.021	0.008	0.002	0.000	0.000
	0.052	0.012	0.008	0.003	0.001	0.000	0.000	0.000

Class L -

SV	1	2	3					
1	71191	1079	58.06	14.71	1.138	0.239	0.022	0.004
2	562.6	51.64	7.827	1.557	0.208	0.030	0.004	0.001
	41.34	7.283	2.545	0.569	0.110	0.018	0.003	0.000
3	11.73	1.551	0.669	0.181	0.042	0.029	0.002	0.000
	1.364	0.262	0.125	0.042	0.011	0.003	0.000	0.000
	0.259	0.040	0.023	0.008	0.003	0.001	0.000	0.000
	0.036	0.006	0.004	0.002	0.001	0.000	0.000	0.000
	0.006	0.001	0.001	0.000	0.000	0.000	0.000	0.000

Fig. 7. HVS weighted variance distribution and proposed subvector configurations

One of the advantages of partitioning the blocks into subvectors is that bits can be assigned efficiently. Vectors with large variances can be assigned more bits and those with smaller variances fewer bits. Table 1 shows a possible bit assignment for the subvector construction of Fig. 7 for an average bit rate of 0.7 bpp.

Table 1 Bit allocations for subvectors of each class

Sub Vector	Class H		Class V		Class D		Class L	
	Dim. k	bits	Dim. k	bits	Kim. k	bits	Kim. k	bits
1	1	8	1	8	1	8	1	8
2	2	10	1	8	2	10	2	10
3	2	8	2	8	3	9	7	8
4	3	8	3	8	5	9		
5	6	9	4	8	6	8		
6	6	8	5	8	9	9		
7	7	8	10	9	9	8		

In Table 1, 'Dim. k' implies vector dimension and the bits indicate the codebook size i.e., the number of code vectors $=2^{bits}$. DC coefficient for all classes is uniformly quantized to 8 bits. The subvectors are vector quantized using the corresponding codebooks. Codebooks are generated for each subvector from a training sequence which is sufficiently long and contains most of the features found in naturally generated images. The codebook design was done using the LBG algorithm [4].

2. Progressive Image Transmission

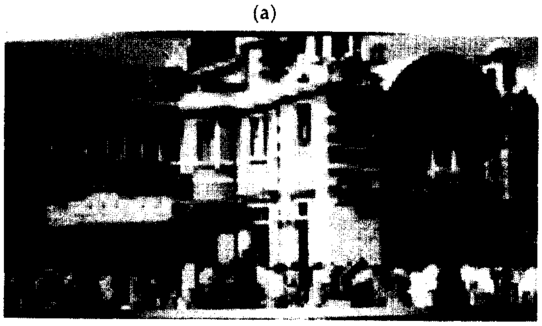
Progressive image transmission is receiving attention for application in interactive image communication over restricted data rate channels [11],[15]. In progressive image transmission, the basic information which can represent each block is first transmitted quickly with as few bits as possible. Upon the receiver's request, the image can be progressively improved with further transmission in several stages until the final required quality is achieved. This technique allows an approximate image to be constructed quickly and the details to be transmitted progressively through several passes over the image. Since our LOT/CVQ scheme contains a hierarchical multi stage structure, it allows progressive image transmission. The coefficients corresponding to the DC value of each class are scalar quantized, transmitted first and reconstructed to zeroth stage for original image approximations. Next successive subvectors of each class are vector quantiged, transmitted and reconstructed to improve the previous approximations.

Ⅳ. Simulation Results

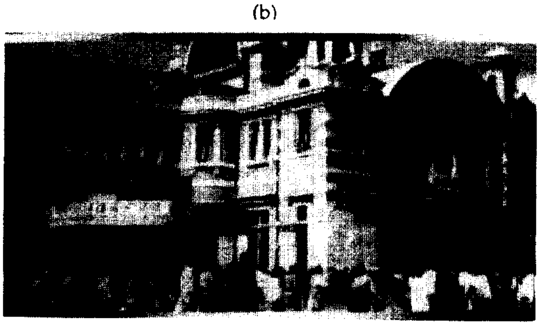
The PIT using LOT/CVQ with HVS weighting is applied to encode two of monochrome images of size 512×512 pixels with 256 gray levels. The original image first undergoes 8×8 LOT and then the transformed image blocks are classified and partitioned into subvectors. The class information for each block is included in the coded image so that reconstruction is possible. This overhead information indicates to the decoder which codebook set has to be used and also the way in which the subvectors have to be recombined to form the entire 8×8 block. For classification into four classes, the overhead information is 4096 $\log_2 4=8192$ bits. This corresponds to an overhead bit rate of 0.031 bpp. Codebooks are generated by LBG algorithm using four different training images, Baboon, Boat, Lady/flower and Martha. The bit allocation for each of the subvectors and the total number of bits depend on the target output bit rate. A similar coding scheme using DCT was introduced by Nam and Rao [12]. The coding of images was done at target average bit rates of 0.7 bpp (including overhead for classification information) using DCT/CVQ for subjective and objective comparision with LOT/CVQ scheme at each progressive stage. Fig. 8 shows the original Seoul station which is composed of two 512×512 images and Fig. 9 the progressive approximations at each stage and error images at 0.5 bpp for comparision between DCT and LOT / HVS / CVQ.

Fig. 8. The original two 512×512 Seoul station image

(a)



(b)

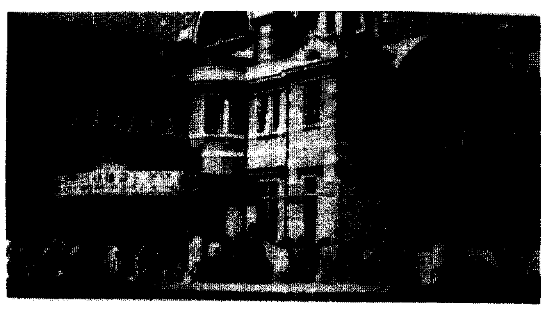


(c)

(d)

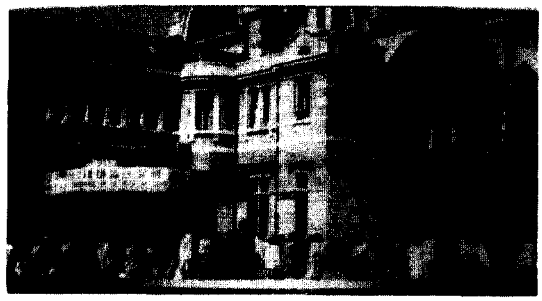
(e)

(f)

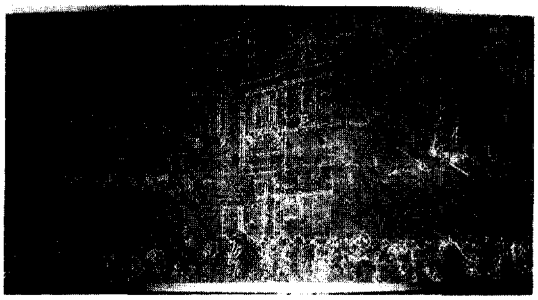


(g)

(h)

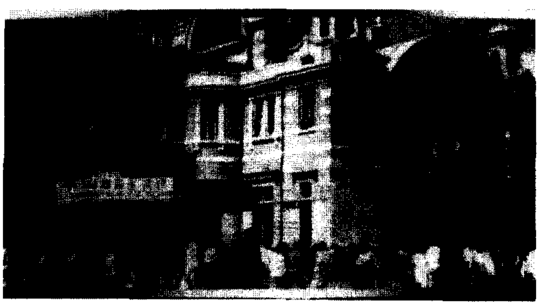


(l)



(i)

(j)



(k)

Fig. 9. Progressive stages and error image at 0.5bpp
(a)the zeroth stage using DCT/HVS/CVQ at 0.16 bpp
(b)the zeroth stage using LOT/HVS/CVQ at 0.16 bpp
(c)the first stage using DCT/HVS/CVQ at 0.31 bpp
(d)the first stage using LOT/HVS/CVQ at 0.31 bpp
(e)the second stage using DCT/HVS/CVQ at 0.43 bpp
(f)the second stage using LOT/HVS/CVQ at 0.43 bpp
(g)the third stage using DCT/HVS/CVQ at 0.50 bpp
(h)the third stage using LOT/HVS/CVQ at 0.50 bpp
(i)the error image (amplified by 5) of DCT/HVS/CVQ at 0.50 bpp
(j)the error image (amplified by 5) of LOT/HVS/CVQ at 0.50 bpp
(k)the sixth stage using DCT/HVS/CVQ at 0.70 bpp
(l)the sixth stage using LOT/HVS/CVQ at 0.70 bpp.

It can be clearly seen that the block artifact and boundary discontiuity between images are reduced significantly, and the quality of the reconstructed image is superior for the LOT/HVS/CVQ scheme especially at low bit rates compared to the DCT/HVS/CVQ technique. For the evaluation of the objective performance the normalized PSNR (peak signal to noise ratio) is used, which is defined as follows

$$PSNR = 10\left(\log_{10}\frac{\sum_{i,j=0}^{N-1} 255^2}{\sum_{i,j=0}^{N-1}(x_{ij}-\hat{x}_{k,ij})^2}\right)\ dB \qquad k = 0, 1, \cdots \qquad (12)$$

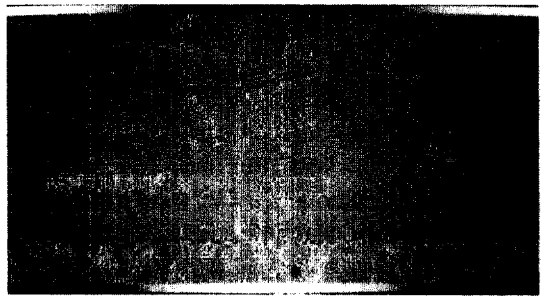
where x_{ij} and $\hat{x}_{k,ij}$ represent the (i,j) th element of the original image and the kth approximation, respectively. The tabulated results (Table 2) show that the LOT / HVS / CVQ exhibits an improvement at each progressive stage over DCT / HVS / CVQ.

Table 2 Bit rates and PSNR values for DCT/HVS/CVQ, LOT/HVS/CVQ and LOT/CVQ at each progressive stages

k	Bit rate bpp	PSNR(dB)		
		DCT/HVS/CVQ	LOT/HVS/CVQ	LOT/CVQ
1	0.16	19.7	20.1	20.1
2	0.31	21.7	22.6	22.6
3	0.43	23.7	24.4	25.9
4	0.50	25.2	26.4	27.6
5	0.57	25.9	27.8	28.4
6	0.63	26.1	28.7	29.0
7	0.70	26.1	29.1	29.2

Fig. 10 shows reconstructed and error image at 0.5 bpp without applying HVS weighting in subvector configuration. It is shown that PSNR of LOT / HVS / CVQ is lower than that of LOT / CVQ, but subjective image quality is better as can be seen from the error images in Fig. 10 because the sharp discontinuous edges are eliminated by HVS weighting.

(a)



(b)

Fig. 10. Reconstructed and error images at 0.5 bpp without HVS weighting in subvector configuration
(a)the third stage using LOT / CVQ at 0.5 bpp
(b)the error image (amplified by 5) at 0.5 bpp.

V. Conclusions

A progressive image transmission scheme using a classified transform coding using LOT and VQ (LOT / CVQ) is developed and compared with the DCT / CVQ scheme. For VQ, subvector partitioning was performed adaptively based on the significance of transform coefficients to HVS. The simulation tests, both subjective and objective, show that the LOT / CVQ reduces block artifacts and LOT / HVS / CVQ makes the subvector configurations more clear resulting in subjectively improved reconstructal images. This is due to the overlapping basis functions of the LOT and adaptive selection for subvector configurations with HVS weighting. As seen from the images in Fig. 9 and from Table 2, the reconstructed approximations rapidly converge to a good quality both subjectively and objectively. This scheme is particularly well suited for interactive image communications over low bandwidth channels.

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