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A Novel Hybrid Linear Predictive Coding – Discrete Cosine Transform based Compression

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***Abstract*—**Image compression is a type of data compression applied to digital images, for reducing the cost for their storage and transmission. Algorithms may take advantage of Algorithms may take advantage of visual perception and the statistical properties of image data to provide superior results compared with generic compression methods. Image compression may be lossy or lossless. Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clip art, or comics. Lossy compression methods, especially when used at low bit rates, introduce compression artifacts. Lossy methods are especially suitable for natural images such as photographs in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate. Lossy compression that produces negligible differences may be called visually lossless. On useful technique used for lossy compression is the discrete cosine transform (DCT) that helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform in the sense that it transforms a signal or image from the spatial domain to the frequency domain. This paper proposes a hybrid lossy compression technique using Linear Predictive Coding (LPC) and Discrete Cosine Transform (DCT) to provide superior compression ratios.

***Keywords*-** *Lossless Predictive Coding , Compression, Discrete Cosine Transform, Inverse Discrete Cosine Transform, PSNR*

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I. INTRODUCTION

Digital Image processing is a technique to perform some operations on an image so as to get an enhanced image or to extract some useful information from it. It is a form of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too. Image processing basically includes the following three steps viz. importing the image via image acquisition tools, analysing and manipulating the image, and obtaining the output in which the result can be altered image or report that is based on image analysis.

There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction.

The objective of digital image compression [1]-[10] is to minimize the redundancy of an image and to store or transmit data through the network in an efficient form. It is also used to reduce the size in bytes without affecting the quality of the original image. It has been classified into lossless [11]-[18] and lossy image compression [19]-[31]. In lossless image compression, original image is exactly reconstructed after the decompression process. It is mainly preferred for archival purpose and often for medical images, icons, clip arts, comics or technical drawings. In lossy compression, the constructed image is not exactly the same as the original image. Rather, the reconstruction is traded with efficiency of compression. Lossy compression is mainly used to compress multimedia applications such as image, audio and video which are used for activity of internet and media. The most important work is reducing redundancy and irrelevancy.

There are many lossy techniques that operate directly on the pixels of an image and thus are spatial domain methods. There is, however, a family of popular compression standards that are based on transforms. Transform coding is a type of data compression for natural data like audio signals or photographic images. The transform is typically lossy, resulting in a lower quality copy of the original input. In transform coding, knowledge of the application is used to choose information to discard, thereby lowering its bandwidth. The remaining information can then be compressed via a variety of methods, when the output is decoded, the result may not be identical to the original input, but is expected to be close enough for the purpose of the application. Several transform coding algorithms are found in the literature for obtaining a good level of compression including Discrete Cosine transforms [21],[22],[28]-[31], Karhunen-Loeve Transforms [23] and Wavelet Transforms [24]-[27],[32]. This paper proposes a transform based coding method using the Discrete Cosine Transform and Lossless Predictive Coding, an improvement over the standard JPEG algorithm.

The rest of the paper is arranged as follows. The methodology has been given in section II while the experimental results have been presented in section III. The conclusion is given in section IV.

II. METHODOLOGY

The Discrete Cosine Transform and the Lossless Predictive Coding are hybridized in a common framework to produce a new lossy compression method. The block diagram of the proposed methodology is shown in Fig. 1.

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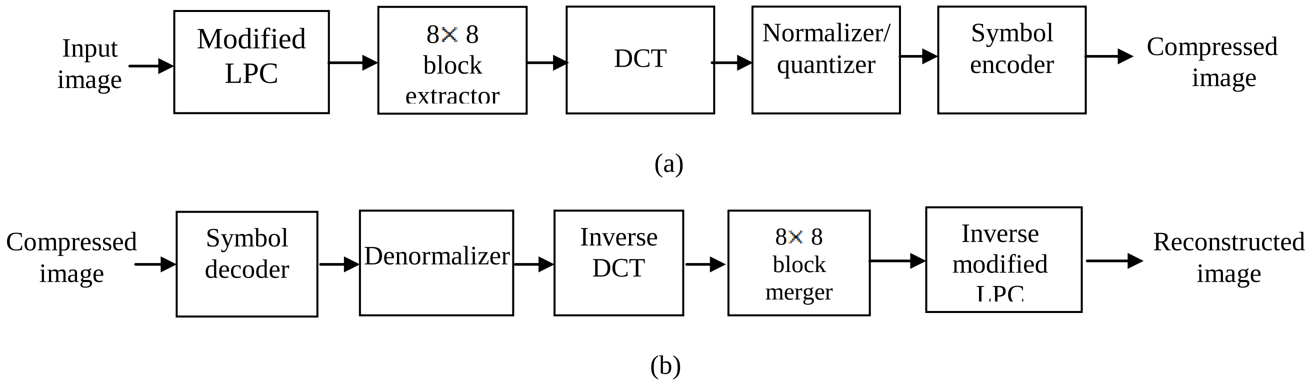

Fig. 1. Block Diagram of Hybrid LPC-DCT Compression Method (a) Encoder (b) Decoder

As shown in Fig. 1, the proposed compression method has been organized in two parts: the coding part and the decoding part. The steps involved in the HLPCDCT method for both coding and decoding are as follows:

A. CODING

Stage 1: Application of the modified Lossless Prediction coding. In the normal method, the first column was taken as reference and the differences were along the horizontal direction. In the modified case, after processing in the horizontal direction, the first column is itself predictive coded which further improves the performance of the system.

Stage 2: Sub-division of the input image into non-overlapping pixel blocks of size of 8x8, which are then subsequently processed left to right, top to bottom. The reason for selecting 8x8 block size can be understood from Fig.6. 4 which illustrates graphically the impact of subimage size on DCT coding reconstruction error. The data plotted are obtained by dividing the 512x512, 8-bit monochrome image 'Lena' into subimages of size n x n, for n= 2,4,8, 16,…, 256,512, computing the transform of each subimage, truncating 75% of the resulting coefficients, and taking the inverse transform of the truncated arrays. It can be seen that the cosine curve flattens as the size of the subimage becomes greater than 8 x 8. Therefore, the optimum size of the subimage is 8 x 8.

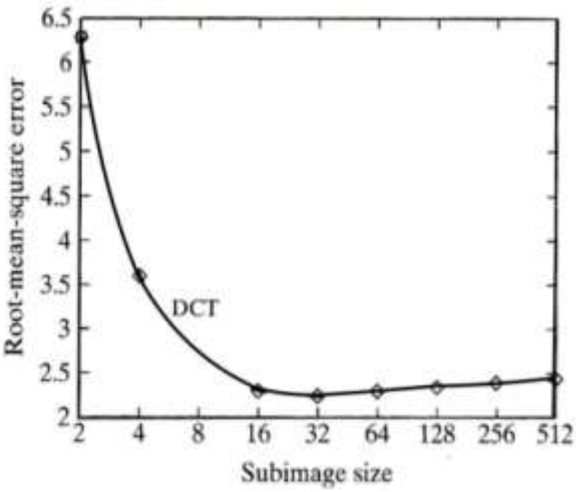

Fig. 2. Reconstruction Error versus Subimage Size for DCT

Stage 3: Level shifting of the image for better coding: As each 8x8 block or subimage is processed, its 64 pixels are level shifted by subtracting 2^{N-1} where $2^N$is the number of gray levels in the image. Level shifting is done in order to make the data fit the discrete cosine transform. This results in the 8-bit pixels falling in the range of -127 to 128 thereby making the data symmetric across zero. This is useful for DCT as any symmetry that is exposed will lead towards better entropy compression. Effectively, this shifts the DC coefficients to fall more in line with value of the AC coefficients. It should however be noted that the AC coefficients produced by the DCT are not affected in any way by this his level shifting.

Stage 4: Computation of the 2-D DCT of the level-shifted image: The 2D DCT of the input image X(*i j*) is taken to get G(*k*, *l*). The DCT matrix of order 8 is given as follows:

0.3536	**0.3536**	**0.3536**	**0.3536**	**0.3536**	**0.3536**	**0.3536**	**0.3536**
0.4904	**0.4157**	**0.2778**	**0.0975**	**-0.0975**	**-0.2778**	**-0.4157**	**-0.4904**
0.4619	**0.1913**	**-0.1913**	**-0.4619**	**-0.4619**	**-0.1913**	**0.1913**	**0.4619**
0.4157	**-0.0975**	**-0.4904**	**-0.2778**	**0.2778**	**0.4904**	**0.0975**	**-0.4157**
0.3536	**-0.3536**	**-0.3536**	**0.3536**	**0.3536**	**-0.3536**	**-0.3536**	**0.3536**
0.2778	**-0.4904**	**0.0975**	**0.4157**	**-0.4157**	**-0.0975**	**0.4904**	**-0.2778**
0.1913	**-0.4619**	**0.4619**	**-0.1913**	**-0.1913**	**0.4619**	**-0.4619**	**0.1913**
0.0975	**-0.2778**	**0.4157**	**-0.4904**	**0.4904**	**-0.4157**	**0.2778**	**-0.0975**

The 2-D DCT of *X*(*i j*) is given by

$$G(k, l) = \text{round}\,(h \times X(i\,j) \times h^T) \qquad (1)$$

Stage 5: Normalization and Quantization of DCT coefficients: The coefficients obtained ins step 4 are then simultaneously normalized and quantized in accordance with

$$Q(u,v) = round\left(\frac{G(k,l)}{q(u,v)}\right) \qquad (2)$$

where the quantization matrix q(*u*,*v*) is given as

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$$q(u,v) = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 12 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

Fig. 3. A Typical Normalization Matrix

and Q (u, v) for u,v = 0, 1, 2, 3,….7 are the resulting normalized and quantized coefficients , G(k,l) is the DCT of an 8x8 block of image f(x,y), and q(u,v) is a transform normalization array. By scaling $q(u,v)$, a variety of compression ratios and reconstructed image qualities can be achieved.

Stage 6: Pattern directed reordering of the normalized coefficients: After each block's DCT coefficients are quantized, the elements of $Q(u,v)$ are reordered in accordance with the zigzag pattern of Fig. 4.

0	1	5	6	14	15	27	28
2	4	7	13	16	26	29	42
3	8	12	17	25	30	41	43
9	11	18	24	31	40	44	53
10	19	23	32	39	45	52	54
20	22	33	38	46	51	55	60
21	34	37	47	50	56	59	61
35	36	48	49	57	58	62	63

Fig. 4. Zigzag Pattern

Since the resulting one-dimensionally reordered array (of quantized coefficients) is qualitatively arranged according to increasing spatial frequency, the symbol encoder of Fig. 1 is designed to take advantage of the long runs of zeros that normally result from the reordering. In particular, the nonzero AC coefficients (i.e. all $Q(u,v)$ except u= v = 0) are coded using a variable length code that defines the coefficients value and number of preceding zeros.

Stage 7: Application of Huffman Coding: The DC coefficients are difference code relative to the DC coefficient of the previous subimage. Default AC and DC Huffman coding tables are provided by the standard, but custom tables and normalization arrays can be or have been constructed, which may be adapted to the characteristics of the image being compressed.

B. DECODING

Stage 1: To decompress a compressed subimage, the decoder must first recreate the normalized transform coefficients that led to the compressed bit stream. Because a Huffman-coded binary sequence is instantaneous and uniquely decodable, this step is easily accomplished in a simple look-up table manner.

Stage 2: The obtained array is now denormalized by using the following equation:

$$(k,l) = \mathrm{Q}(u,v).* \, \mathrm{q}(u,v) \qquad \textbf{(3)}$$

Stage 3: The partial reconstructed subimage is obtained by taking the inverse DCT of the denormalized array in accordance with equation 2 and 3 and then level shifting each inverse transformed pixel by 2^N.

Stage 4: Finally the inverse LPC operation is applied to obtain the complete reconstructed image.

IV. EXPERIMENTAL RESULTS

The performance of this technique is measured using compression ratio (CR), Peak-signal-noise-ratio (PSNR) and root-mean- square error (RMSE). Visual inspection is also carried out on the compressed images as to judge the effectiveness of the compression method. A wide range of quality factor ranging from 1 to 12 was taken for the six images and the results tabulated and compared with the standard JPEG results and shown in Table 1.

TABLE 1
Compression Results for 'Lena' Image

Quality	**JPEG**	**Proposed Method**	**JPEG**	**Proposed Method**
	Compression Ratio(CR)		**PSNR**	
1	9.8729	10.5195	41.3594	39.9417
2	18.1716	19.7079	34.7799	33.4624
3	24.8195	26.1038	32.8510	31.2459
4	26.9695	29.0249	31.6603	30.6712
5	32.9741	34.6697	30.7721	29.5641
6	38.9979	41.5760	29.9159	28.9548
7	43.0733	44.5973	29.2170	28.2354
8	46.6614	50.9834	28.6674	27.7851
9	51.8276	54.7701	27.9780	27.9815
10	56.6186	60.9726	27.4986	26.9842
11	59.9049	64.8624	27.0469	26.2314
12	64.1881	69.0248	26.7658	26.2314

It can be seen from the above table that the proposed algorithm performs significantly better than the conventional JPEG at almost all levels of quality factor. Fig.5 illustrates the qualitative results at different quality levels for 'Lena' image.

Quality = 1
(a)

Quality =3
(b)

Quality = 5
(c)

Quality = 7
(d)

Quality = 9
(e)

Quality = 11
(f)

Fig. 5. Restoration Results of HLPC-DCTC for 'Lena' Image for Different Values of Quality (a) Quality = 1 (b) Quality =3 (c) Quality =5 (d) Quality =7 (e) Quality =9 (f) Quality = 11

The hybrid Linear Predictive Coding –Discrete Cosine Transform compression technique proposed in this section is competitively better than the JPEG algorithm at all levels of quality. However, like the JPEG algorithm, it also suffers from blocking artifacts as the value of quality increases.

IV. CONCLUSION

A Novel Hybrid lossy compression technique has been proposed in this technique which incorporates the Linear Predictive Coding and the Discrete Cosine Transform. The simulations were carried out for a number of benchmark images including Lena, Peppers, Barbara, Lighthouse, Mandrill and Grass. In each of these cases, it was found that the results obtained from this technique were superior to that obtained from JPEG at various levels of quality factor.

However, like the JPEG algorithm, it also suffers from artefacts. Future work may be directed at removing these artifacts and reducing the processing time.

REFERENCES

[1] R. C. Gonzalez and R. E. Woods, "Digital Image Processing", 2nd edition, *Prentice Hall*, 2002.

[2] R. C. Gonzalez, R. E. Woods and S. L. Eddins, "Digital Image Processing Using MATLAB", *Pearson*, 2004.

[3] K. R. Castleman, "Digitial Image Processing", *Pearson*, 1996.

[4] M. Petrou and C. Petrou, "Image Processing –The Fundamentals", 2nd edition, *Wiley*, 2010.

[5] A. Bovik, "Handbook of Image and Video Processing", *Academic Press*, 2000.

[6] O. Marques, "Practical Image and Video Processing Using MATLAB", *IEEE Press, Wiley*, 2011.

[7] S. Jayaraman, S. Esakkirajan and T Veerakumar, "Digital Image Processing", *Tata McGraw Hill*, 2009.

[8] K. Sayood, "Introduction to Data Compression", *Elsevier*, 2006.

[9] J. M. Blackledge and M. J. Turner, "Image Processing II- Mathematical Methods, Algorithms and Applications", *Horwood Publishing Series: Mathematics and Applications*, 2000.

[10] J. M. Blackledge and M. J. Turner, "Image Processing III-Mathematical Methods, Algorithms and Applications', *Horwood Publishing Series: Mathematics and Applications*, 2001.

[11] S. W. Golomb, "Run-length encodings", IEEE Transactions on Information Theory, Vol. IT-12, pp. 399401, July 1966.

[12] G. Motta, J. A. Storer, and B. Carpentieri, "Lossless image coding via adaptive linear prediction and classification", Proceedings of the IEEE, Vol. 88, No.11, pp. 1790-1796, 2000.

[13] Aleksej Avramovic and Salvica Savic,"Lossless Predictive Compression of Medical Images", Serbian Journal of Electrical Engineering, Vol. 8, no.1, pp. 27-36, Feb. 2011.

[14] I. H. Witten, R. Neal, and J. M. Cleary, "Arithmetic Coding for Data Compression", Communications of the ACM, Vol. 30, no. 6, pp. 520540, June 1987.

[15] D. A. Huffman, "A method for the construction of minimum redundancy codes", Proceedings of the IRE, Vol. 40, no. 9, pp. 10981101, September 1952.

[16] R. Hashemian , "High Speed Search and Memory Efficient Huffman Coding," IEEE Inter. Symp. Circuit Syst. May 3-6, 1993.

[17] R. Hashemian,"Design and Hardware Implementation of a Memory efficient Huffman Decoding", EEE Consumer Elec. August Vol. 40, No.3, 1994, pp. 345-352.

[18] S. B. Choi, Moon Ho Lee "A Fast Huffman Decoder via Pattem Matching", 1994 IEEE Intemational Workshop on ISPACS, 1994, PP 134-138.

[19] P. C. Cosman, E. A. Riskin, R. M. Gray, "Combining vector quantization and histogram equalization", Informal. Processing Manag., vol. 28, no. 6, pp. 681-686, Nov.—Dec. 1992.

[20] P. A. Chou, T. Lookabaugh, R. M. Gray, "Entropy-constrained vector quantization", IEEE Trans. Acoust. Speech Signal Processing, vol. 37, pp. 31-42, Jan. 1989.

[21] A. J. Ahumada, H. A. Peterson, "Luminance-model-based DCT quantization for color image compression", Human Vision Visual Processing and Digital Display III, vol. 1666, pp. 365-374, 1992.

[22] H. A. Peterson, A. J. Ahumada, A. B. Watson, "An improved detection model for DCT coefficient quantization", SPIE Proceeding, vol. 1913, pp. 191-201, 1993.

[23] A. K. Jain, "A fast Karhunen-Loeve transform for a class of random processes", IEEE Trans. Comm., vol. COM-24, pp. 1023-1029, Sept. 1976.

[24] I. Daubechies, "Ten Lectures on Wavelets", *Society for Industrial and Applied Mathematics, Philadelphia*, 1992.

[25] S. Mallat, "A Wavelet Tour of Signal Processing", 2nd edition, *Academic Press*, 1999.

[26] S. Mallat, "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, Vol. 11, No. 7, pp. 674–693, Jul. 1989.

[27] R. M. Rao and A. S. Bopardikar, “Wavelet Transforms- Introduction to Theory and Applications”, *Pearson Education*, 2002.

[28] W.-H. Chen, C. Smith, S. Fralick, "A fast computational algorithm for the discrete cosine transform", IEEE Trans. Commun., vol. 25, no. 9, pp. 1004-1009, Sep. 1997.

[29] Z. Xiong, O. G. Guleryuz, M. T. Orchard, "A DCT-based embedded image coder", *IEEE Signal Process. Lett.*, vol. 3, pp. 289-290, Nov. 1996.

[30] D. Nister, C. Christopoulos, "An embedded DCT-based still image coding algorithm", *IEEE Signal Process. Lett.*, vol. 5, pp. 135-137, Jun. 1998.

[31] P. Telagarapu, V.J. Naveen, A.L Prasanthi, G.V. Santhi, "Image compression using DCT and wavelet transformations", *Int. J. of Signal Processing Image Processing and Pattern Recognition*, vol. 4, no. 3, 2011.