IMAGE COMPRESSION WITH 2D DISCRETE COSINE TRANSFORM AND SPARSE 3D DISCRETE COSINE TRANSFORM

Renu Rani*

Monika**

ABSTRACT:

In this paper, an algorithm for image coding based on a sparse 3-dimensional Discrete Cosine Transform (3D DCT) is studied. This is essentially a method for achieving a sufficiently sparse representation using 3D DCT. The simulation results obtained by the algorithm are compared to the 2D DCT. From simulation it is shown that the algorithm, that uses DCT but in 3 dimensions, outperforms the 2D DCT used in JPEG standard and achieves comparable results but has a limitation of line pattern.

Keywords: Sparse image coding, 2 dimensional DCT, 3 dimensional DCT, DWT.

* Asst. Prof, Department of ECE, KITM, Karnal, India

** Asst. Prof, Department of ECE, SGI, Samalkha, India

1. Introduction

In data compression reducing or removing redundancy or irrelevancy in the data is of great importance. An HVS [6] is more sensitive to energy component with low spatial frequency than with high spatial frequency. Therefore, compression can be achieved by quantizing the coefficients, so that important coefficients (low-frequency coefficients) are transmitted and the remaining coefficients are discarded. Different mathematical transforms, have been considered for the task [3]. The JPEG standard which is based on Discrete Cosine Transform (DCT) is widely used for both lossy and lossless image compression, especially in web pages. However, the use of the DCT on 8×8 blocks of pixels results sometimes in a reconstructed image that contains blocking effects.

In other words, the signal is sparsely represented in the transform domain coefficients, and hence by preserving a few high magnitude transform coefficients that convey most of information of the signal and discarding the rest, the signal can be effectively estimated. The sparsity of representation depends on the type of the transform used and also on the signal properties. In fact the wide variety in natural images makes impossible for any fixed 2D transform to achieve good sparsity for all cases. Thus, the commonly used transforms can achieve sparse representations only for particular image patterns. In this article an image coding strategy based on an enhanced sparse representation in transform domain is studied which is based on a recently proposed approach [5] for image denoising. From this approach an enhanced sparse representation can be achieved by grouping similar 2D fragments of input image (blocks) into 3D data arrays. We used this approach with a 3D DCT transform for image coding purposes. The procedure includes five steps: grouping of image in 8x8 blocks, conversion of blocks into 3D array, 3D DCT transformation of a 3D array, shrinkage of the transform domain coefficients, and inverse 3D DCT transformation. Due to the similarity between blocks in a 3D array, the 3D DCT transform can achieve a highly sparse representation. Experimental results demonstrate that it achieves outstanding performance in terms of both PSNR and sparsity.

The paper is organized as follows. The section 2 describes DCT. The section 3 describes the main idea of sparse 3D DCT and discusses its algorithm. Finally,

Section 4 provides some experimental results of algorithm and its comparison with DCT.

2. The Discrete Cosine Transform (DCT)

The Discrete Cosine Transform was first proposed by Ahmed et al. (1974). DCT coefficients measure the contribution of the cosine functions at different discrete frequencies. DCT [11][8] provides excellent energy compaction. In DCT, the image is divided into blocks of $N \times N$samples and each block is transformed independently to give $N \times N$ coefficients [7]. The most common DCT definition of a 1-D sequence of length N is [9]:

$$Y[K] = C[K] \sum_{n=0}^{N-1} X[n] \, Cos \left[\frac{(2n+1)\pi n}{2N} \right] \qquad (1)$$

For k= 0, 1, 2,…,$N-1$

Likewise, the inverse DCT transformation 1-D sequence of is defined as

$$Y[K] = \sum_{n=0}^{N-1} C[K] X[n] \, Cos \left[\frac{(2n+1)\pi n}{2N} \right] \qquad (2)$$

For k= 0, 1, 2,…, $N-1$. C [K] is given by:

$$C[K] = \sqrt{\frac{1}{N}} \quad \text{for } k = 0$$

$$\sqrt{\frac{2}{N}} \quad \text{for } k = 1, 2, \ldots\ldots N-1$$

The 2-D DCT is simply a direct extension of the 1-D case and is given as

$$Y[j,k] = C[j]C[k] \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} X[m,n] \cos\left[\frac{(2m+1)j\pi}{2N}\right] \cos\left[\frac{(2n+1)k\pi}{2N}\right] \qquad (3)$$

Where: j, k = 0,1,2,…,N −1 and. The inverse transform is defined as:

$$X[m,n] = \sum_{j=0}^{N-1}\sum_{k=0}^{N-1} C[j]C[k]\, Y[j,k] \cos[\frac{(2m+1)j\pi}{2N}]\ \cos[\frac{(2n+1)k\pi}{2N}] \quad (4)$$

For many blocks within the image, most of the DCT coefficients will be near zero. DCT in itself does not give compression. To achieve the compression, DCT coefficients should be quantized so that the near-zero coefficients are set to zero and the remaining coefficients are represented with reduced precision that is determined by quantizer scale. Increasing the quantizer scale leads to high compression and poor decoded image quality [2].

3. Sparse 3D- Discrete Cosine Transform

This algorithm shows, that only uses DCT but in 3 dimensions, performs better than DCT used in JPEG standard and achieves comparable results (but still less than) the wavelet transforms. This image coding strategy is based on Sparse 3D transform [3] which is a recently proposed approach for image denoising [5].

Based on this approach an enhanced sparse representation can be achieved by grouping similar 2D fragments of input image (blocks) into 3D data arrays. This approach is used with a 3D DCT transform for image coding purposes. Grouping can be realized by various techniques like K-means clustering, self-organizing maps, vector quantization fuzzy clustering and others. The procedure includes three steps: 3D DCT transformation of a 3D array, contraction of the transform domain coefficients, and inverse 3D DCT transform. Due to the similarity between blocks in a 3D array, the 3D DCT transform can achieve a highly sparse representation.

The Algorithm

```
 // Algorithm for sparse 3D DCT
{
 Divide input image to blocks of 8 × 8 fragments and Save blocks in
Y.
while (Y is not empty)
  {
    For ( i=1,...,Number Of Fragments)
```

{

Choose one block as a reference block (Y_r)

and Calculate $d(Y_r, Y_i) = \frac{|Yr-Yi|2}{N^2}$

were Y_i is the i^{th} block.

}

if $d(Y_r, Y_i) \leq$ Threshold Distance

{

Assign Y_i to a group and Remove Y_i from Y

Save resulted group in a 3D array named as

Group Array

}

for every group of Group Array Perform a 2D DCT

on that group

Then Perform a 1D DCT on the third dimension of

Group Array

if (Transform Domain Coefficients $\leq$ Hard

Threshold)

{

Discard that coefficient.

}

Perform inverse 3D DCT transform

}

Place each decoded block on its original position.

}

//End of Algorithm

4 Simulation Results

The coding of this paper is done in MATLAB R2010a. In this paper, we compared discrete cosine transform (DCT) and sparse 3D DCT. The quality of a compression method could be measured by the traditional distortion measures such as the peak signal to-noise ratio (PSNR), signal to noise ratio (SNR), Mean square error (MSE), energy retained(ER) and execution time (ET). We compared the performance of these transforms on image "friends (64 x 64)". Fig.7 shows the reconstructed images of DCT, HAAR & sparse 3D DCT.

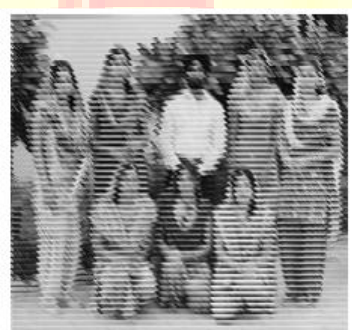
Table 1: shows the various parameters for DCT, Sparse 3D DCT

Transforms	Energy retained	Percentage of Zeros	SNR(db)	Mean Square error	PSNR(db)	Execution time(sec)
DCT	99.9324	67.5293	48.1648	117.2808	27.4385	0.8112
Sparse 3D DCT	99.9990	88.7531	85.9067	0.3327	52.9107	87.5010

Figure 1 shows the original images and their decoded versions using 2D DCT and sparse 3D DCT for Table 1. As it can be seen from figure 1 (b), the blocking effect when 2D DCT is used is clearly visible. But when 3D DCT is used there is almost no blocking effect. It can also be seen from figure 1 (c) that in case of Sparse 3D DCT recovered image has some line pattern. In Figures 1, 2 and 3, a comparison between the performances of these two transforms is made for test image.

(a)

(b)



(c)

Figure1. (a) Original image, (b) Compressed by DCT, (c) Compressed by 3D DCT

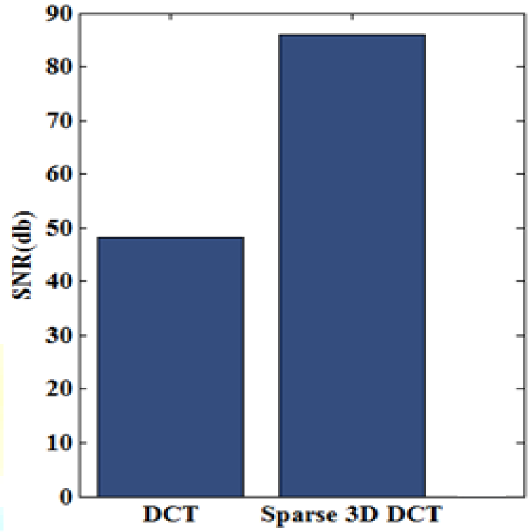


Figure 2: Performance of DCT and Sparse 3D DCT in terms of SNR (db)

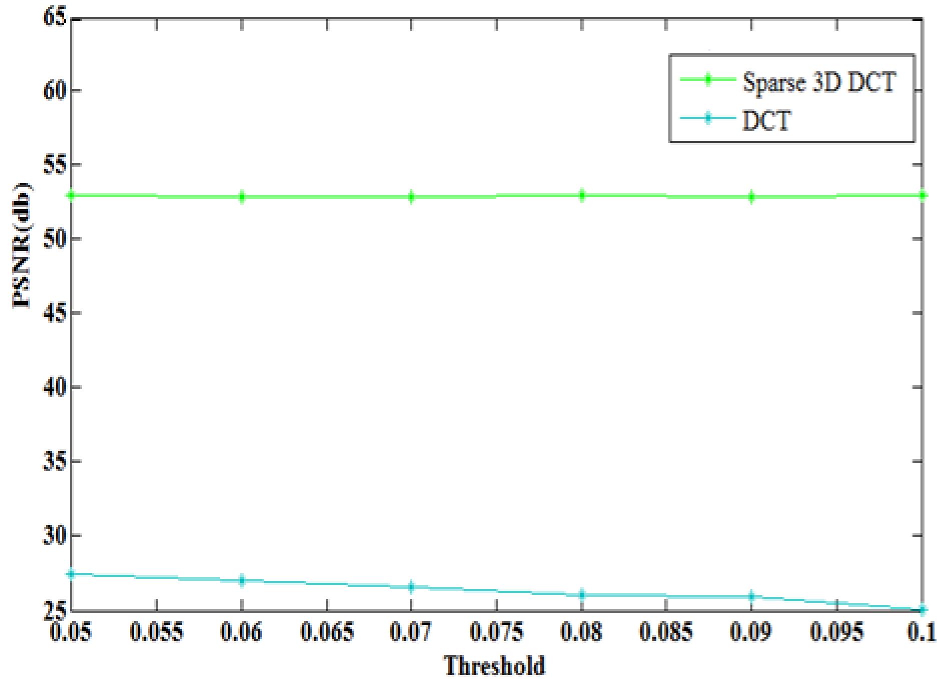


Figure 3: Plot of PSNR (db) Vs threshold for DCT and Sparse 3D DCT

5. CONCLUSIONS AND FUTURE WORK

In this paper we have implemented the idea presented in [4] and compared it with DCT. The DCT shows its good results in terms of execution time, energy compaction & percentage of zeros. But SNR, PSNR and MSE are not acceptable. So, to improve all the parameters Sparse 3D-DCT is implemented. Sparse 3D DCT technique gets its basic idea from a denoising technique. This idea is based on 3D DCT transform to enhance the sparsity of the coefficients. Results show that Sparse 3D DCT outperforms DCT used in JPEG standard but at the cost of execution time. The one more drawback of Sparse 3D DCT is that recovered image has some line pattern which can be improved by using Discrete Wavelet Transform DWT [1][10]. Another improvement can be possible by using adaptive thresholding. In adaptive thresholding, different thresholds are chosen for different regions in the image.

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