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DISCRETE COSINE TRANSFORMATION FOR ANALYSIS OF IMAGE

***Rahul Lande, [1]Prof. Sudha Nair**
*,[1] RKDF Institute of Science and Technology, Bhopal (M.P), India

ABSTRACT

Digital image processing remains a challenging domain of programming. There are several transforms that do image transformation. Image compression is very important for efficient transmission and storage of images . Demand for communication of multimedia data through the telecommunications network and accessing the multimedia data through Internet is growing explosively. Many algorithms and VLSI architectures for the fast computation of DCT have been proposed. A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering. I can perform discrete cosine transformation by different algorithms, in this paper we use pixels processing. In this paperI have implement method for image transformation and analysis using discrete cosine transformation technique and develop results using matlab coding. In future the MATLAB code can be converted to VHDL code and implement on FPGA kit inorder to develop ASIC (application specific IC) for image transformation and analysis. This will give a generalization to image processing.

Keywords: ASIC, image transformation, discrete cosine transformation, VHDL

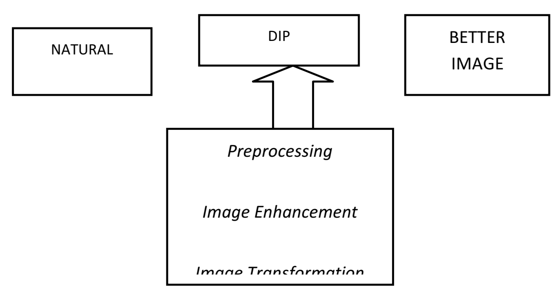
INTRODUCTION

Digital Image Processing

Most of the common image processing functions available in image analysis systems can be categorized into the following four categories:

- Preprocessing
- Image Enhancement
- Image Transformation
- Image Classification and Analysis

Corresponding Author*
Email- Rahullande15aug@gmail.com
sudhanair7@rediffmail.com



A. Preprocessing: Preprocessing functions involve those operations that are normally required prior to the main data analysis and extraction of information, and are generally grouped **as** radiometric or geometric corrections**.**

B. Image enhancement: The objective of the second group of image processing functions grouped under the term of image enhancement is solely to improve the appearance of the imagery to assist in visual interpretation and analysis. Examples of enhancement functions include contrast stretching to increase the tonal distinction between various features in a scene, and spatial filtering to enhance (or suppress) specific spatial patterns in an image.

C. Image transformations: These are operations similar in concept to those for image enhancement. However, unlike image enhancement operations which are normally applied only to a single channel of data at a time, image transformations usually involve combined processing of data from multiple spectral bands. Arithmetic operations (i.e. subtraction, addition, multiplication, division) are performed to combine and transform the original bands into "new" images which better display or highlight certain features in the scene.

D. Image classification and analysis operations are used to digitally identify and classify pixels in the data. Classification is usually performed on multi-channel data sets (A) and this process assigns each pixel in an image to a particular class or theme (B) based on statistical characteristics of the pixel brightness values. There are two types of redundancies that occur in images. They are spatial and spectral redundancy. Spatial redundancy is due to the correlation between neighboring pixels. Spectral redundancy is due to correlation between different color planes. Both spatial and as well as spectral redundancies can be removed using subband coding or transform coding (Discrete Cosine Transform) which are two well-known techniques. There is other type of redundancy called temporal redundancy which is due to the correlation of different frames in a sequence of images such as in videoconferencing applications or broadcast images. These temporal redundancies are removed by an interframe coding called Motion Compensated Predictive Coding.

DCT is a computation intensive operation. Since DCT approaches the statistically optimal Karhunen-Loeve Transform (KLT) for highly correlated signals [13]. DCT is used in most of the digital processing application because of its energy compaction characteristics. The development of efficient algorithms for the computation of DCT (more specifically DCT –II) began soon after Ahmed et al (1974) [14] reported their work on DCT. It was natural for initial attempts to focus on the computation of DCT by using Fast Fourier Transform (FFT) algorithms. Many algorithms for fast computation of DCT are reported in the literature. General approach used in DCT is converting the image pixels of block 8x8 or 16x16 into series of coefficients that define spectral composition of the block. Its direct implementation requires large number of adders and multipliers. Conventional approach used for 2-D DCT is row-column method. This method requires 2N 1-D DCT‘s for the computation of NxN DCT and a complex matrix transposition architecture which increases the computational complexity as well as area of the chip. On the other hand if the DCT processor is designed using polynomial approach [13,16] reduces the order of computation as well as the number of adders and multipliers used in the DCT processor will be reduced and area reduction can be considerably achieved. Thus the main objective of this paper work is to design a DCT processor in which area reduction is achieved using pipelined hardware architecture using reusability concept.

METHODOLOGY

In this paper, I have done image transformation based on pixel processing, which includes

- image compression
- histogram equalization

A. Image Compression:

Number of bits required to represent the information in an image can be minimized by removing the redundancy present in it. There are three types of redundancies: (i) spatial redundancy, which is due to the correlation or dependence between neighboring pixel values; (ii) spectral redundancy, which is due to the correlation between different color planes or spectral bands; (iii) temporal redundancy, which is present because of correlation between different frames in images. Image compression research aims to reduce the number of bits required to represent an image by removing the spatial and spectral redundancies as much as possible.

Data redundancy is of central issue in digital image compression. If n1 and n2 denote the number of information carrying units in original and compressed image respectively, then the compression ratio CR can be defined as:

CR=n1/n2;

And relative data redundancy RD of the original image can be defined as

RD=1-1/CR;

Three possibilities arise here:

(1) If n1=n2, then CR=1 and hence RD=0 which implies that original image do not contain any redundancy between the pixels.

(2) If n1>>n1,then CR→∞ and hence RD>1 which implies considerable amount of redundancy in the original image.

(3) If n1<<n2,then CR>0 and hence RD→-∞ which indicates that the compressed image contains more data than original image.

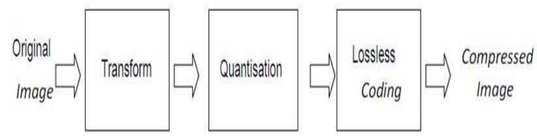


Image Compression model

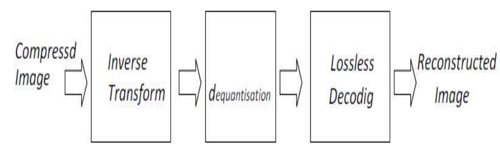


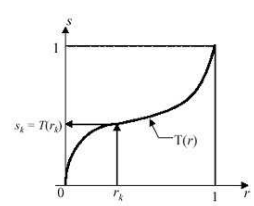
Image Decompression model

B. Histogram Equalization: Suppose that the pixel values are continuous quantities that have been normalized so that they lie in the interval [0, 1]. The variable r represents the gray-level in the image to be enhanced, with r = 0 representing black and r = 1 representing white.

For any r in the interval [0, 1], consider a transformation of the form s = T(r). The transformation produces a level s for every pixel value r in the original image. It is assumed that this transformation function satisfies the following two conditions:

(a) T(r) is single-valued and monotonically increasing in the interval 0 < r < 1; and

(b) 0 < T(r) < 1 for 0 < r < 1.



The inverse transformation from s to r is denoted by

$r = T^{-1}(s) \qquad 0 < s < 1$

The assumption is that $T^{-1}(s)$ also satisfies conditions (a) and (b) with respect to the variables. The gray-levels in an image may be viewed as random quantities in the interval [0, 1].In the continuous case, the

original and the transformed gray-levels can be characterized by their probability density functions $p_r(r)$ and $p_s(s)$ respectively.
Using probability theory, if $p_r(r)$ and $T(r)$ are known and $T^{-1}(s)$ satisfies condition (a), then

$p_s(s) = p_r(r)\, dr/ds$

where $r = T^{-1}(s)$ (1)

Most of the enhancement techniques are based on modifying the appearance of an image by controlling the probability density function of its gray-levels via the transformation function T(r).
Consider,

$$s = T(r) = \int_{-\infty}^{0} p_r(w)dw + \int_{0}^{r} p_r(w)dw + \int_{r}^{\infty} p_r(w)dw$$

, where $0 \le w \le r \,\&\, 0 \le r \le 1$

This is recognized as cumulative-distribution function (CDF) of r

$$\frac{ds}{dr} = p_r(r)$$

$$\frac{dr}{ds} = \frac{1}{p_{r(r)}}$$

Substituting dr/ds into Eq. (1) yields:

$$p_s(s) = \left[p_r(r)\frac{1}{p_r(r)}\right]_{r=r^{-1}(s)} = [1]_{r=r^{-1}(s)}$$

$$= 1 \quad 0 \le s \le 1$$

Which means that we have a uniform density in the interval of definition. This is important, because it is not always possible to obtain $T^{-1}(s)$ analytically. Also, this shows that using the transformation function equal to the cumulative distribution of r produces an image whose gray-levels have a uniform density. To be able to use this technique for images, we need to discretize gray-levels. Accordingly, the technique used to obtain uniform histograms is called "histogram equalization" or "histogram linearization".

$$p_r(r_k) = \frac{n_k}{n}, \qquad 0 \le r_k \le 1 \; and k = 0, 1, \dots \dots, L-1$$

$$s_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n} = \sum_{j=0}^{k} p_r(r_j), \qquad \begin{cases} 0 \le r_k \le 1 \\ k = 0, 1, \dots L-1 \end{cases}$$

EXPERIMENTAL WORK AND SIMULATION

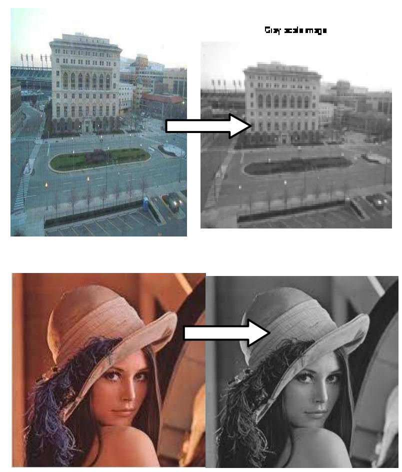
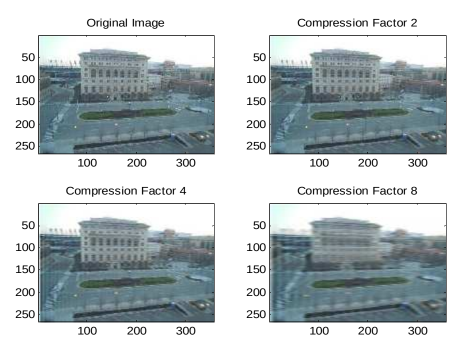


Fig 1: Conversion of RGB image to Gray Scale Image



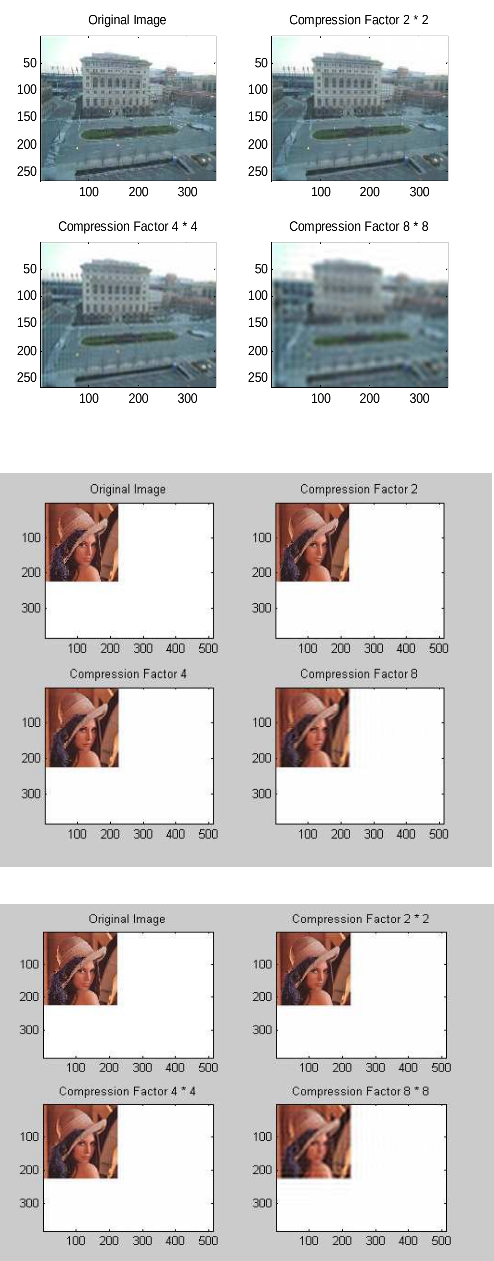


Fig. 2: Image Compression with compression factor 2,4&8 and 2*2,4*4 & 8*8

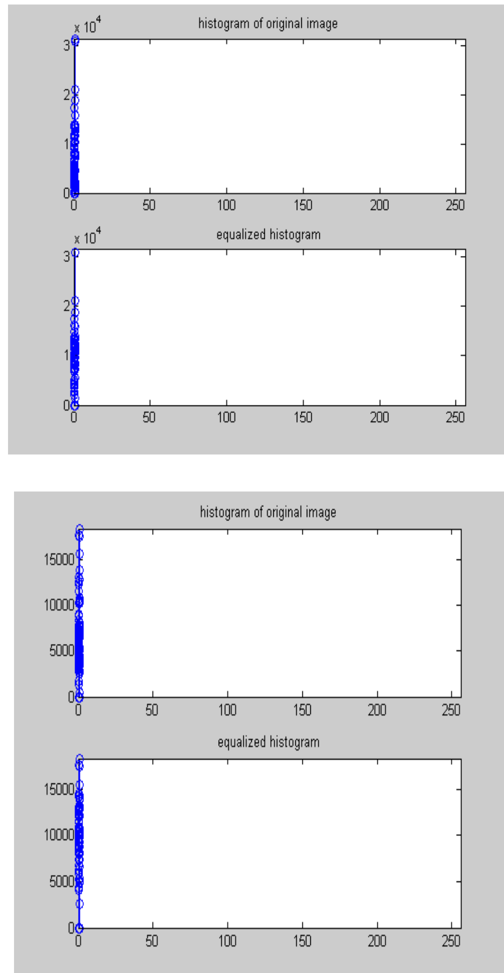
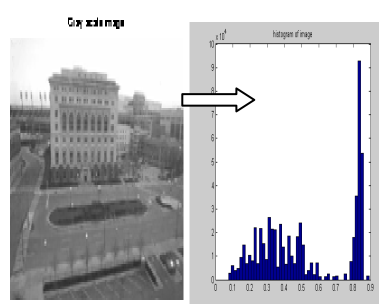


Fig. 3: Histogram and equalized histogram of taj and Lenaimage



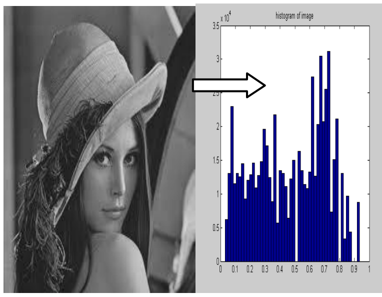


Fig. 4: Histogram of Originals Image

RESULT AND DISCUSSION

There are several transforms that do image transformation. In this paper we use discrete cosine transformation. Mostly discrete cosine transformation is used for compression of images but in this paper we use discrete cosine transformation for image analysis i.e for, image compression and histogram equalization .Pixel based processing is easy to perform as well as it will give accurate results in comparison to other methods. We have taken two images one that is available on system and the other which is taken from the digital media and then downloaded to the computer. Their occurs difference in the processing of two images i.e the image which is already available has got aligned pixels than the image that is downloaded from the digital media.

CONCLUSION

Presently only software's using different algorithms and different software languages are used for image transformation but in this paper we suggested for the development of an ASIC meant for image analysis. This paper will give a generalized method for image transformation, and analysis based on pixel processing.

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