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Image Compression using DWT and Principal Component Analysis

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***Abstract*: *A block wise implementation of principal component algorithm is suggested din the base work. The main disadvantage with the earlier work is that it takes time as the size of the image increases and further looping due to blocking effect of the algorithm. The compression performance reduces as the block size reduces or no. of block increases. In order to solve the mentioned problems, the images are decomposed using the discrete wavelet transform using haar wavelet. The global principal component analysis algorithm is applied on LH and HL frequency sub-band images. This enables the compression by preserving the critical boundaries or contours that are to be preserved while compressing the image so that minimum information is lost in compression during thresholding process.*

***Index Terms*: *PCA→ Principal Component Algorithm, PCA→ Principal Component Analysis, DWT→ Discrete Wavelet Transform*

I. Introduction

PICTURES are the representation of a particular scene. Images can be of many types such as graphic, optical, mental etc. If we talk about digital images then these are the images that can be stored on hard disk. Pictures are the most common and convenient means of conveying or transmitting information. They portray spatial information that can be recognized as an object.

II. Related Works

In the paper entitled “Combined Sparse Representation Based on Curvelet Transform and Local DCT for Multi-layered Image Compression” proposed a new multi-layered representation technique for image compression which combine curvelet transform and local DCT in order to benefit from the advantages of each. He proposed morphological component analysis (MCA) method to separate the image into two layers, piecewise smooth layer and textured structure layer, respectively associated to curvelet transform and local DCT. Each layer is encoded independently with a different transform at a different bit rate. [1]

In the paper entitled “A Novel Image Deblocking Method Based on Curvelet Transform” described that an Image block effect is due to the quantification process using Discrete Cosine Transform (DCT) to compression coding, which dumps some frequency, and leads to noticeable discontinuous leaps. A deblocking algorithm based on curvelet transform is proposed in this paper. [2]

In the paper entitled “Laplacian Pyramid Versus Wavelet Decomposition for Image Sequence Coding” presented that there have been many applications in the multiresolution representations for image processing and data compression. Several approaches have been developed on this domain using different ways, the most widely used are sub-band decompositions with filter banks and pyramid transforms. [3]

The presented paper reviews the different techniques for image compression and presents a comparison in a tabular way. Spatial as well as frequency domain techniques are discussed here in detail. Further, different transform like curvelet, wavelet and dct are discussed in detail as image compression algorithm. [4]

In the paper entitled “Image Compression using Digital Curvelet Transform” presented a novel approach to digital image compression using a new mathematical transform, the curvelet transform. The transform has shown promising results over wavelet transform for 2-D signals. Wavelets, though well suited to point singularities have limitations with orientation selectivity, and therefore, do not represent two-dimensional singularities (e.g. smooth curves) effectively. [5]

In the paper entitled “Curvelet Transform Based Embedded Lossy Image Compression” described that Curvelet transform is one of the recently developed multiscale transform, which possess directional features and provides optimally sparse representation of objects with edges. He proposed an algorithm for lossy image compression based on the second generation digital curvelet transform. [6]

In the paper entitled “Curvelet-based Image Compression with SPIHT” proposed a new compression methodology, which uses curvelet coefficients with SPIHT (Set Partitioning in Hierarchical Trees) encoding scheme. The first phase deals with the transformation of the stimulus image into the curvelet coefficients. [7]

Discrete cosine transform in combination with principal component analysis algorithm is discussed here for hyper spectral image compression. Appreciable improvement in psnr and compression ratio is observed using the proposed algorithm. [8]

In the paper entitled "A New lossless Image Compression Technique based on Bose, Chandhuri and Hocquengham (BCH) Codes" presented an efficient lossless image compression approach that utilizes BCH coding with compression. The use of BCH code improves the results of the Huffman algorithm in terms of increasing the compression ratio. Therefore, the experiment confirms that the proposed technique is suitable for compression of text, image and video files and would be useful in numerous network applications. [9]

In the paper entitled "Fast and Efficient Medical Image Compression Using Contourlet Transform" presented a Wavelet based contourlet image compression algorithm. In the diagnosis of medical images, the significant part (ROI) is separate out from the rest of the image using fuzzy C- means algorithm and then to the resultant image optimized contourlet transform is applied to enhance the visual quality. The regions of less significance are compressed using Discrete Wavelet transform. To the resultant image Huffman coding is applied to get the compressed image. [10]

In the paper entitled "A Novel image fusion method using Contourlet Transform" introduced a novel image fusion algorithm based on contourlet transform. The principal of contourlet and its good performance in expressing the singularity of two or higher dimensional are studied. Experiments show that the proposed method works better in preserving the edge and texture information than wavelet transform method and laplacian pyramid methods do in image fusion. [11]

In the paper entitled "Fusion of Multimodality Medical Images using Combined Activity Level Measurement and Contourlet Transform" described a novel combined Activity Level Measurement (ALM) and Contourlet Transform (CNT) for spatially registered, multi-sensor, multi- resolution medical images. [12]

In the paper entitled "A Novel image deblocking method based on Curvelet transform" presented the algorithm which processes the curvelet coefficients separately which are obtained by curvelet transform of the degraded images to recovery the images. The coefficients corresponding to block effect of the original image can be found for every layer and different layers using different methods. [13]

In the paper entitled "SAR and panchromatic image fusion based on region features in nonsubsampled contourlet transform Domain" presented a novel fusion algorithm based on the imaging characteristic of the SAR image. The algorithm performs the different fusion rules for each particular region independently. [14]

In the paper entitled "Performance Analysis of Multi Source Fused Medical Images using Multi resolution transforms" described that the image fusion combines information from multiple images of the same scene to get a composite image that is more suitable for human visual perception or further image processing tasks. The fused output obtained after the inverse transform of fused sub band coefficients. [15]

III. Image Acquisition and Preprocessing

Principal Components Analysis (PCA) is a mathematical formulation used in the reduction of data dimensions. Once patterns are found, they can be compressed, i.e., their dimensions can be reduced without much loss of information. In summary, the PCA formulation may be used as a digital image compression algorithm with a low level of loss. The reduced dimension computational structure is selected so that relevant data characteristics are identified with little loss of information. Such a reduction is advantageous in several instances: for image compression, data representation, calculation reduction necessary in subsequent processing, etc.

Use of the PCA technique in data dimension reduction is justified by the easy representation of multidimensional data, using the information contained in the data covariance matrix. The description of Principal Component Analysis is made by means of the explanation of eigen values and eigenvectors of a matrix.

Following steps are carried out in order to compress the given input image using PCA:

Step-1: Convert the RGB image into gray scale Image i.e. (8-bit) color format. The gray image format is a row x column matrix of color intensities in 8- bit size.

Step-2: Centering of the Image is done by computing the mean of the image intensity and then subtracting each pixel gray value from mean gray value.

$$MeanI = \frac{1}{row\ x\ col}\sum_{r=1}^{row}\sum_{c=1}^{col} I(r,c)$$

$$\text{Centered Image CI(r,c)} = \sum_{r=1}^{row}\sum_{c=1}^{col}(MeanI - I(r,c))$$

Step-3: The covariance of the CI is computed by the following expression:

$$CovImg = CI(r,c) * CI(r,c)^T$$

Where CI(r,c)T is the transpose of the matrix CI(r,c).

Step-4: The eigen values and eigen vectors of the covariance matrix are computed by using the following expression:

$$A.V=\lambda.V$$

Where, A= :m x m matrix (Gray Image matrix)
V= m x 1 non-zero vector (Eigen Vector)
Λ :scalar (Eigen Values)

Any value of λ for which this equation has a solution is called the eigen value of A and the vector V which corresponds to this value is called the eigen vector of A.

Step-5: A.V = λ.V
A.V - λ.I.V=0
(A - λ.I).V=0

Finding the roots of |A - λ.I| will give the eigen values and for each of these eigen values there will be an eigen vector.

Step-6: A threshold is selected and eigen value less than the threshold are removed. Or in other words, largest eigen values and corresponding eigen vectors are extracted out based on some threshold values. These are called the principal components of the image (centered image).

Step-7: Now, based on the principal components, the image can be divided into different eigen vectors as follows:

$$Image = \begin{bmatrix} Eigen\ Vector-1 \\ Eigen\ Vector-2 \\ Eigen\ Vector-3 \\ \ldots \end{bmatrix}$$

Largest eigen vector images are stored as principal image components and is the compressed image.

IV. Quality Metrics for Performance Evaluation

For judging the performance of an image Compression techniques and comparison with proposed work, some quality measures have been developed as follows:

Peak-Signal-to-noise ratio (PSNR):

The peak-signal to noise ratio (PSNR) was used to evaluate the reconstructed image quality. The PSNR is defined as follows:

$$PSNR = 10 \log 10 \quad \frac{2552}{\frac{1}{NxN}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(f\,(i,j) - f'\,(i,j))\,2} \qquad (1.5)$$

Where, m × n is the size of the original image and f (i,j) and f'(i,j) are the gray-level pixel values of the original and reconstructed images, respectively.

Standard Deviation (SD): The standard variation of an image is given by:

$$\sigma 2 = \frac{1}{MxN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x\,(I,j) - \mu)2 \qquad (1.6)$$

This corresponds to the degree of deviation between the gray levels and its mean value, for the overall image.

3). Entropy E: The expression of the information entropy of an image is given by:

$$H = -\sum_{i=0}^{L-1} p_i \log p_i \qquad (1.7)$$

Where L denotes the number of gray level, pi equals the ratio between the number of pixels whose gray value equals i (0 to L - 1) and the total pixel number contained in an image. The information entropy measures the richness of information in an image.

V. Results

The presented algorithm is implemented on matlab version 7.5. A data base of 100 pair of ear's image is prepared in jpeg format. The results show accuracy above 95% in identifying the correct query image from that of data base image. The standard deviation and entropy are the fair performance measure based on which the distinction could be achieved. However, more statistical features could be added to increase the uniqueness when the data base becomes large.

Table 1: Standard Deviation and Entropy of Query Image with respect to data base images

Query Image	Data Base Image	SD	Entropy
1	15	0.021	1.203
2	20	0.023	1.142
3	18	0.009	1.112
4	5	0.011	1.283

Keeping the same query image, the processing time is computed for different size data base and is tabulated below:

Table2: Processing Time Estimate

Query Image	Data Base Size	Processing Time (Secs.)
1	25	10 Secs.
1	50	25 Secs
1	75	60 Secs.
1	100	95 Secs.

VI. Conclusion

The results show a fair accuracy in identification of the query image to its respective data base image and are 95% accurate. However, it is observed that as the data base size increases, the processing time increases proportionately. This is due to lot of matrix reshaping, arithmetic calculation and looping etc. The processing time may be improved with some parallel algorithm development for the same.

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