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Hybrid Techniques On Color And Multispectral Image For Compression

C. Senthilkumar*
Associate Professor & Ph.D (Scholar)
Department of Computer Science,
Erode Arts & Science College (Autonomous),
Erode, Tamil Nadu, India
csincseasc@gmail.com

Dr. S. Pannirselvam
Research Supervisor & Head
Department of Computer Science,
Erode Arts & Science College (Autonomous),
Erode, Tamil Nadu, India
pannirselvam08@gmail.com

Abstract—Image Compression is a technique to reduce the number of bits required to represent and store an image. This technique is also used to compress two dimensional color shapes without loss of data as well as quality of the Image. Even though Simple Principal Component Analysis can apply to make enough compression on multispectral image, it needs to extend another version called Enhanced PCA(E-PCA). The given multispectral image is converted into component image and transformed as Column Vector with help of E-PCA. Covariance matrix and eigen values are derived from vector. Multispectral images are reconstructed using only few principal component images with the largest variance of eigen value. Then the component image is divided into block. After finding block sum value, mean value, the number of bits required to represent an image can be reduced by E-BTC model. The features are extracted and constructed in Table form. The proposed algorithm is repeated for all multispectral images as well as color image in the database. Finally, compression ratio table is generated. This proposed algorithm is tested and implemented on various parameters such as MSE, PSNR. These experiments are initially carried out on the standard color image and are to be followed by multispectral imager using MATLAB.

Keywords— *Enhanced Principal Component Analysis(E-PCA), multispectral image, component image, eigen value, eigen vector, SV, MV, E-BTC, Mean Square Error(MSE), Peak Signal to Noise Ratio(PSNR).*

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I. INTRODUCTION

Multispectral image are images of the same object taken in different bands of visible or infrared region of the electromagnetic spectrum. Images are acquired for remote sensing applications are generally known as multispectral in nature. Multispectral image typically contains information outside the normal human perceptual range[27]. This type of image may include infrared, ultraviolet, x-ray, acoustic or radar data. These are not images in the usual sense because the information is not directly visible by the human system.

If more than three bands of information are in the multispectral images, the dimensionality is reduced by applying PCT [Principal Component Transform]. Most of the satellites currently in orbit collect image information in 2 to 12 spectral bands; Source of these types of images include underwater sonar system, airbone radar, infrared imaging, medical diagnostics imaging system. The Principal Component Analysis(PCA) is one of the most successful technique that has been used in image recognition and compression. It is also used for data reduction and feature extraction analysis[3].

Data compression has been a major issue in today's everywhere commodity computing and communication environment. The main goal of compression is to store higher amount of data using lesser amount of memory space so that the data can be sent over a networks with fewer memory but higher speed and efficiency.

In this paper Section I introduces the basic concept of multispectral image and image compression. Section II describes literature review. Section III discusses Principal Component Analysis and BTC pitfalls. Section IV focuses on theoretical foundation for PCA and BTC. Section V explains proposed methodology.Section VI explains the experimental results and conclusion was presented in Section VII.

II. Literature Review

Principal Component Analysis (PCA) [3], [4] was first described by Karl Pearson in 1901. The basic concept of PCA is to reduce dimensionality of a data set, which consist of a large number of interrelated variables, while preserving the variations present in the data set as much as possible. This is accomplished by transforming the original set of variables into a new set of variables, called Principal Components (PCs), which are uncorrelated. PCA uses the idea of representing a face vector as a weighted sum of basis vectors. It was introduced in [19] and was applied to face recognition [20]. We consider a face image as a point in a high dimensional space. One number of dimensions is equal to number of pixels in the face image. The set of training images form a face cluster in the high dimensional space. PCA finds out a subspace for the cluster such that it has maximum energy stored. The directions corresponding to maximum data variations are the eigen vectors of the covariance matrix for the face cluster.

Fisher's Linear Dimensional Analysis or LDA [21] is a class specific method which discriminates between classes by finding projections such that it maximizes the separation between classes under the constraint that within class variation are minimized. In [24] CCA was used for the segmentation of formational Magnetic Resonance Images; here we apply CCA for the purpose of face recognition. Correlation analysis is useful to find a linear relationship between two sets of variables and CCA creates new variables for the each set such that the correlation between these variables is maximized and independent of affine transformation.

One of the earliest contributions to the field of recognition via subspace decompression was by Sirovich and Kirhy and Turk and Pentland [23].

A multi-linear generation to the 3-way data analysis was proved by Lathauwer et al [22] which has been the primary analysis of the mathematical aspects of Higher Order Singular Value Decompression [HOSVID].

III. Pitfalls In Existing PCA And BTC

A. *Principal Component Analysis:*

Principal component analysis(PCA)[19][25][26]is derived from Karhuneu-Loeve transformation.It's main goal is to find an optimal orthogonal transformations maximizes the rate of decrease of variance of data set.In PCA approaches,the eigen values and eigen vectors are useful to select component.

PCA-Disadvantage:

In the traditional PCA has been widely used for recognition only but not for compression. The existing PCA accounts for all component image so that it takes reasonable execution time to carry out all the component. It supports only low dimensional data. It needs different normalization, different parameter settings, different resolution factors to store the image. It supports only smaller size of image. In PCA, Error rate increases as the number of features increase. Lot of training sets are needed.

To overcome those above problem, the traditional PCA should be extended to another version of PCA which is called Enhanced PCA(E-PCA).

B. *Block Truncation Coding(BTC)-Method*

Block truncation coding(BTC) is a simple and fast lossy compression technique for gray scale images in 1979 Developed by Delp and Mitchell[10]. The original of BTC preserves the standard mean and standard deviation. Various methods have been proposed during last 30 years such as BTC, standard BTC, Absolute Moment Block Truncation Coding(AMBTC).

BTC-Disadvantages:

So for BTC supports for binary image compression and gray scale image compression.

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Since entire image requires large memory, BTC divides into block size 8 x 8,16 x 16 pixels. The transform is not applied to the entire image at a scratch, but it is applied over fixed block with size 8x8,16x16 pixels. BTC can perform mathematical task to evaluate variance, standard deviation, statistical moments a, b.

Hence it needs to overcome those short coming problem, the existing BTC should be extended to multispectral image as well as color images which is called Enhanced BTC(E-BTC).

IV. Theoritical Foundation

Principal Component Analysis

A common problem in statistical image compression is that of feature selection or feature extraction. Feature selection refers to a process whereby a data space is transformed into a feature space. The transformation is designed in such a way that data set may be represented by a number of effective features. Principal Components Analysis known as the Karhuneu-Loeve transformation [1] maximizes the rate of decrease of variance of data set.

1) *Basic Data Representation*

Let X denote an m-dimensional random Vector and q denote unit vector with dimensional m onto which the Vector X is to be projected. This projection is defined by the inner product of the Vector X and q as shown by

$$A = x^T q = q^T x \qquad (1)$$

Subject to the constraint

$$\|q\| = (q^T q)^{1/2} = 1 \qquad (2)$$

The projection A is a random variable with a mean and variance related to the statistics of the random Vector X.

Let the data vector x denote a realization of the random vector *X*. Specifically, from (1), it is noted that

$$a_j = q_j^T x = x^T q_j \qquad j=1,2,\ldots.m \qquad (3)$$

where $a_j$are called the principal components; they have the physical dimensions as the data vector *x*.

2) *Dimensionality Reduction*

Principal components anlaysis provides an effective technique for dimensionality reduction. It may reduce the number of features needed for effective data representations by discarding small variance and retain only those terms that have large variances. Let λ_1, λ_2,λ_3,…,λ_l denote the largest *l* eigen values of the correlations matrix R.

The data vector *x* by truncating after *l*terms as follows

$$\hat{x} = \sum_{j=1}^{l} a_j q_j \qquad (4)$$

$$\hat{x} = [q_1, q_2, \ldots, q_l] \begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ \cdot \\ a_l \end{bmatrix} l <= m \qquad (5)$$

Given the original data vector *x*, the following expression returns the principal components

$$\begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ \cdot \\ a_l \end{bmatrix} = \begin{bmatrix} q_1^T \\ q_2^T \\ \cdot \\ \cdot \\ \cdot \\ q_l^T \end{bmatrix} x, \quad l \leq m \qquad (6)$$

The mapping from the data space to the feature space represents an encoder as shown below

Input Vector — Encoder — Vector of principal components

$$\begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_m \end{bmatrix} \Rightarrow \boxed{\begin{bmatrix} q_1^T \\ q_2^T \\ \cdot \\ \cdot \\ \cdot \\ q_l^T \end{bmatrix}} \Rightarrow \begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ \cdot \\ a_l \end{bmatrix} \qquad (7)$$

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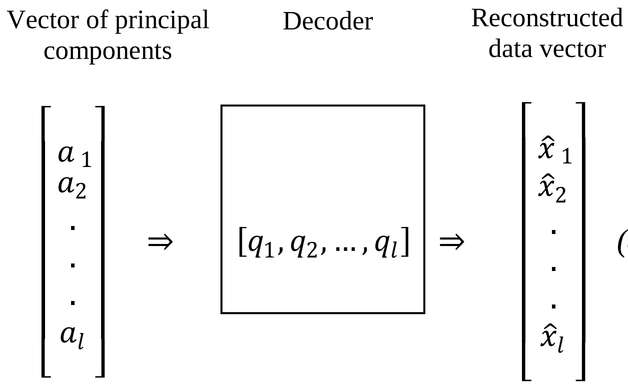

(8)

It is noted that the dominant eigen values $\lambda_1, \lambda_2, \dots, \lambda_l$ determine the number of principal components used for encoding and decoding respectively. And also the eigen values $\lambda_{l+1}, \dots, \lambda_m$ are the smallest Eigen values of the correlation matrix: they correspond to the terms discarded from the (reconstructed) vector. Thus, to perform dimensionality reduction on some input-vector, we compute the eigen values and eigen vectors of the correlation matrix of the input data vector, and then project the data orthogonally onto the subspace belonging to the dominant eigen values.

Let us take on example with two variable x1 and x2 in Fig.1 in a Cartesian coordinate system.

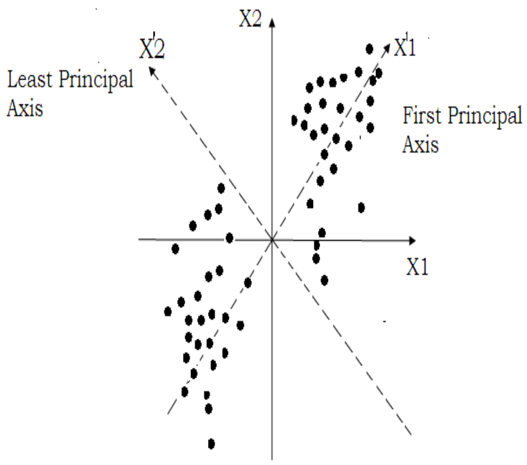

Figure 1: Two principal Components in 2D Plane.

The covariance matrix for this sample data is

$$C = \begin{pmatrix} 287.3 & 167.5 \\ 167.5 & 122.2 \end{pmatrix}$$

The corresponding Eigen values and Eigen vectors are shown in Table 1.

TABLE1: EIGEN VALUE AND EIGEN VECTOR

Component	Eigen Value	Eigen Vector	
		x1	x2
1	391.49	0.849	0.528
2	18.05	-0.528	0.849

Thus the first Principal Component accounts for 391.49/(391.49+18.05)*100=96%. The second PC accounts for only 4% of the spread. Therefore those points projected perpendicularly onto the direction X_1' can still maintain the Principal Components. So the second projected components are discarded.

Assume a multispectral image consists of a total M pixels in N spectral bands. From this transformation, orthogonal unit vectors which called Principal Components are found out.

BTCMETHOD

In existing system Block truncation coding is a well-known compression scheme proposed in 1979 for the grayscale image. The image component is partitioned into non-overlapping 'n' blocks of pixels as shown. For each block, threshold and reconstruction values are obtained. The threshold value is calculated in the concerned block. Then a bitmap of the block is obtained by replacing all pixels are greater than or equal to the threshold by '1' or '0'. Each segment (group of 1's and 0's) in the bitmap, the reconstruction table is formed.

Block truncation coding works by dividing the image into as well as small sub blocks of size 8×8 pixels and then reducing the number of gray levels within each block. The basic form of BTC divides the whole image into 'n' blocks and codes each block using a two-level quantizer. The two level a and b are selected using the mean $\bar{X}$ and standard deviation (σ) of the gray levels within block and are preserved. The $\bar{X}$ and σ are calculated using (9) and (10)

$$\bar{X} = \frac{1}{m}\sum_{i=1}^{m} xi \quad (9)$$

$$\sigma = \sqrt{\frac{\sum y_i - {x_i}^2}{m}} \quad (10)$$

In BTC, two statistical moments a and b are computed using (11) and (12) and are preserved along with the bit plane for reconstructing the image.

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$$a = \bar{X} - \sigma\sqrt{\frac{q}{m-q}} \qquad (11)$$

$$b = \bar{X} + \sigma\sqrt{\frac{m-q}{q}} \qquad (12)$$

Where q is the number of pixel values greater than or equal to $\bar{X}$, and (m-q) is the number of pixels whose gray levels are less than $\bar{X}$ while reconstructing the image, the 'o' in the bit plane is replaced by a and The '1' in the bit is replaced by b.

V. PROPOSED ENHANCED PCA AND EHNANCED BTC METHOD

Image-transform coding is the most popular method used in image-coding applications. An image is linearly transformed to produce a set of linear transform coefficients, which are usually scalar quantity for transmission. Thus, Transform Coding is a mathematical operation that converts a large set of highly correlated [dimensioned] pixels into a smaller set of uncorrelated coefficients. This transformation is done by E-PCA. The E-PCA only selects most important components and discards lesser component without significantly affecting the reconstructed image quality. The purpose of transform coding is to decompose the correlated data into an uncorrelated data.

The transformation 'reorganizes' the gray values of the image and thus changes the correlation properties of the image. The transformation compacts the image information into a small number of coefficients. The following figure shows that block diagram of proposed system for E-PCA and E-BTC.

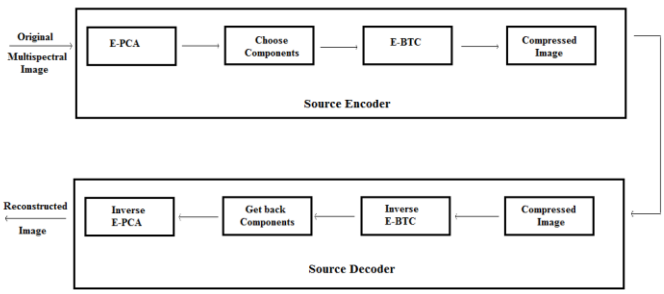

Figure 2: Proposed Compressed and Decompressed diagram

In proposal research work, combination of E-PCA and E-BTC is to reduce to separate the image component, the bit size per pixel, and to improve the quality of the image. This work proposes both techniques to multispectral image and color image. The E-BTC divides image into small as well as sub block with size 2×2 and performs all tasks without mathematical computational parameters so that maximum time consuming is saved. The proposed E-PCA algorithm and E-BTC algorithm are as follows.

Algorithm for E-PCA

Step 1: Get some interrelated data from multispectral image.

Step 2: Construct original vector for the interrelated data.

Step 3: Find the sum and mean of the vector.

Step 4: Construct the Data Adjust Transformation vector.

Step 5: Construct covariance matrix.

Step 6: Calculate Eigen values and Eigen vectors from covariance matrix.

Step 7: Sort the Eigen values from higher to lower in order.

Step 8: Choose components and form feature vector according to Eigen values.

Step 9: Construct Component Transformation matrix.

Step 10: Project all the vectors to the corresponding eigen-subspaces.

Inverse E-PCA

Step 11: Deriving the new data set

$$[Trans\ Data] = \begin{bmatrix} Row\ feature \\ Vector \end{bmatrix} * \begin{bmatrix} Row\ data \\ Adjust \end{bmatrix}$$

Step 12: Getting old data back

$$\begin{bmatrix} Row\ data \\ Adjust \end{bmatrix} = \begin{bmatrix} Row\ Eigen \\ Vector \end{bmatrix}^T * \begin{bmatrix} Trans \\ Data \end{bmatrix}$$

Step 13:
$$\begin{bmatrix} Row\ Original \\ Data \end{bmatrix} = \begin{bmatrix} Row\ Data \\ Adjust \end{bmatrix} + \begin{bmatrix} Original \\ mean\ data \end{bmatrix}$$

The above said E-PCA algorithm is applied on Multispectral image as well as color. Thus E-PCA is used to choose dominant components and to discard the remaining components.

Algorithm for E-BTC

Step 1: Get an individual component image with n×m pixels.

Step 2: Divide the input image into 'm' blocks that each has to small size image f(n×n) with f$(x_1, x_2, x_3, \ldots \ldots x_{n\times n})$ denote the pixel in a block.

Step 3: Calculate m1←(int) first row mean value.

Step 4: Calculate m2←(int) second row mean value.

Step 5: Mean = (int) (m1+m2)/2.

Step 6: If(m1>m2) a=m1; b=m2;

Else a=m2; b=m1;

Step 7: Computation of Binary allocation

$$B(m,n) = \begin{cases} 1: f(n \times n) > mean \\ 0: f(n \times n) \leq mean \end{cases}$$

Step 8: Store Compression Block Table2.

Step 9: Simulate this process until the last Block.

Step 10: End.

Proposed Algorithm for Inverse E-BTC

Step 1: Get Binary allocation matrix B(m,n).

Step 2: Get mean, a, b from compression table.

Step 3: The reconstructed block $\bar{f}$(n,n)

$$= \begin{cases} B(n \times n): 0 \leftarrow a \\ B(n \times n): 1 \leftarrow b \end{cases}$$

Step 4: Store $\bar{f}$(n×n) into Reconstructed Table.

Step 5: Simulate this process until the last block.

Step 6: Finally compression ratio table is generated.

Step 7: Compare proposed experimental ratio with existing BTC compression ratio.

Step 8: Generate graph for proposed and existing method.

Step 9: End.

A compressed block storage contain four values $(mean, a, b, B)$, where mean is average of pixels, a is the average of first row pixels, b is the average of second row pixels and B is bit plane, giving the quantization of the pixel values.

TABLE 2: COMPRESSED BLOCK STORAGE

I \ C	C$_1$	C$_2$	…….	C$_n$
I$_1$	${}^1_1b_1\ldots{}^1_1b_m$	${}^1_2b_1..{}^1_2b_m$	…….	${}^1_nb_1\ldots{}^1_nb_m$
I$_2$	${}^2_1b_1\ldots{}^1_1b_m$	${}^2_2b_1\ldots{}^2_2b_m$	…….	${}^2_nb_1\ldots{}^2_nb_m$
….	….	….	….	….
I$_j$	${}^j_1b_1\ldots{}^j_1b_m$	${}^j_2b_1\ldots{}^j_2b_m$	…	${}^j_nb_1\ldots{}^j_nb_m$

The same structure table is also used for reconstructed image block storage. This also contains the same parameters mean, a, b, B.

VI. SIMILARITY MEASURES

The image to be tested on multispectral are shown in Fig.3 and Fig.4. Fig.5 shows the different format color image database. The difference between the original image and reconstructed image is called Mean Square Error and is calculated using (13). The quality of the reconstructed image called the Peak Signal to Noise Ratio (PSNR) is calculated using (14) and is the inverse of MSE. The compression efficiency is measured by Compression Ratio (CR) or by the bit rate.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2 \qquad (13)$$

$$\text{PSNR} = 10log_{10}\left[\frac{MSE}{255^2}\right] \qquad (14)$$

$$CR = \frac{no.of bytesreq\ .torepresentt\ \ heoriginalimage}{no.of bytesreq\ .torepresentcompressedimage} \qquad (15)$$

where y_i is the reconstructed pixel value, x_i is the original pixel value and N is the number of pixels in an image.

Figure 3: Original multispectral image

Multispectral image

Figure 4: Separated multispectral image

Figure 5: Different color image format database

TABLE 3: COMPRESSION RATIO TABLE FOR EXISTING BTC

Image Names	JPG (%)	BMP (%)	TIFF (%)	PNG (%)	GIF (%)
Apple	84.91	75.23	75.78	77.34	74.11
Bird	81.12	74.31	77.36	74.56	75.32
Dog	81.35	75.47	76.12	78.63	77.11
Flower	83.47	76.58	72.45	75.41	76.23
Human	80.75	73.24	76.74	77.58	78.38

TABLE 4: COMPRESSION RATIO TABLE FOR PROPOSED E-PCA & E-BTC METHOD

Image Names	JPG (%)	BMP (%)	TIFF (%)	PNG (%)	GIF (%)
Apple	89.25	78.88	80	79.14	76.33
Bird	82.56	79.12	79.73	78.63	79
Dog	83.11	78.35	78.69	81.66	78.23
Flower	89.22	78.14	75.34	79.13	79.93
Human	84.54	76.39	78.86	79.65	80.19

TABLE 5: MSE COMPRESSION VALUE

Image Names	JPG	BMP	TIFF	PNG	GIF
Apple	30.37	28.15	32.18	26.82	26.32
Bird	32.03	27.57	24.36	29.7	23.26
Dog	32.24	26.15	27.76	27.14	21.75
Flower	28.87	31.84	36.56	27.32	22.44
Human	30.81	27.61	29.12	25.13	24.85

TABLE 6:PSNR COMPARISON VALUE

Image Names	JPG	BMP	TIFF	PNG	GIF
Apple	38.08	39.69	25.06	37.17	44.75
Bird	28.93	34.63	35.1	29.31	32.15
Dog	26.52	38.58	30.38	32.12	42.15
Flower	36.73	32.38	26.16	22.88	32.49
Human	28.78	36.28	35.01	31.09	31.06

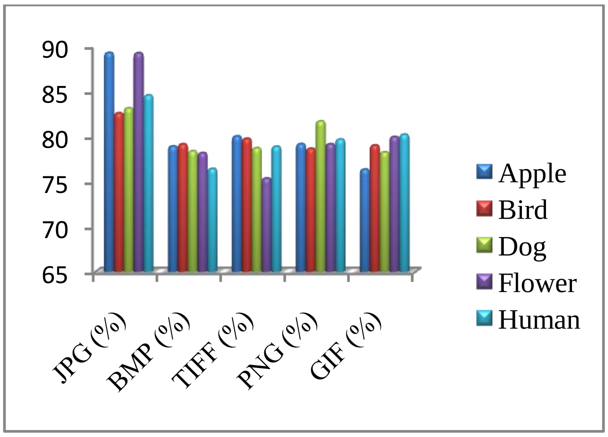

Figure 6: Performance Evaluation for Proposed E-PCA & E- BTC Compression Ratio

VII. CONCLUSION

Due to the limit in the storage medium and transmission bandwidth on multispectral image, the image which is to be used must be within the lesser size. To solve this issue, an image processing technique called image compression is employed. From the observation, it is clear that only 50% of the largest eigen values are sufficient for compression on multispectral image. It is now clear that the both E-PCA and E-BTC are used to reduce the dimensionality of image and the number of bits per pixel. E-PCA provides more effective representation of multispectral image.

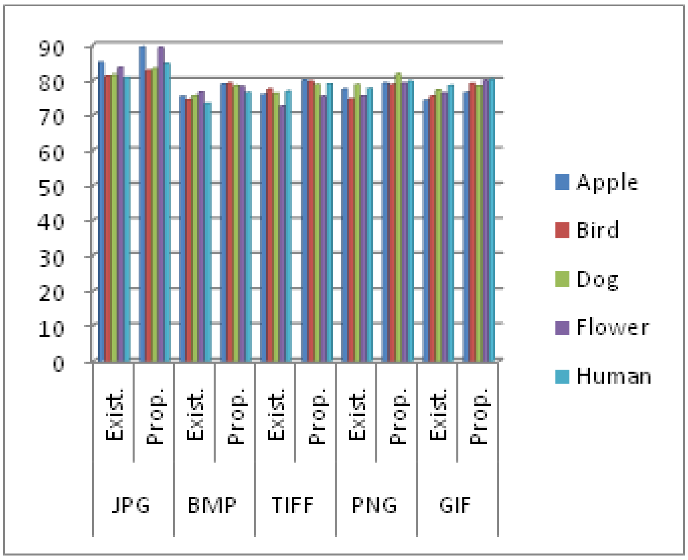

Figure 7:Comparison of Existing and Proposed Compression Ratio

The most important components are occupied in the high order statistical information among the pixels. On the basis of various set of experiments, the proposed algorithm gives better results compared to existing method. The proposed E-PCA and E-BTC can overcome some drawbacks existed in the traditional E-PCA and E-BTC. The proposed technique results in better compression ratio and also it requires lesser amount of time for processing.

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AUTHORS PROFILE

Dr. S. Pannirselvam was born on June 23rd 1961. He is working as Associate Professor and Head, Department of Computer Science in Erode Arts & Science College (Autonomous), Erode, Tamilnadu, India. He is research supervisor for M.Phil and Ph.D programmes. His area of interests includes, Image Processing, Artificial Intelligence, Data Mining. He has presented more than 25 papers in National and International level conferences.

Prof.C.Senthilkumar was born on January 10th1963. He is working as Associate Professor, Department of Computer Science in Erode Arts & Science College (Autonomous), Erode, Tamilnadu, India. He has obtained his Masters degree in Computer Science and M.Phil degree in Computer Science from Alagappa University, Karaikudi. He is research supervisor for M.Phil programmes. His interest area includes Image Processing, Data Mining and Neural Networks.He has presented 4 papers in National and one International level.