RESEARCH ARTICLE

Compression Techniques and Face Recognition with PCA: A Study

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Abstract- Face recognition presents a challenging problem in the field of image analysis and computer vision. It has received a great deal of attention over the last few years because of its many applications in various domains. Disk storage space is one of the most fundamental challenges in designing biometric system. Due to limited bandwidth and storage capacity, images must be compressed before storing and transmitting. In biometrics datasets, facial images are usually stored in JPEG compressed format and should be fully decompressed to be used in a face recognition system. In case of face recognition application, to reduce computational complexity of JPEG decompression step, we are directly dealing with face recognition in compressed domain. Many techniques are available for compressing the images. But in some cases these techniques will reduce the quality and originality of image. This paper addresses various compression techniques as it is applicable to various fields of image processing and compressed domain face recognition using principle component analysis.

Keywords- Compression techniques, Lossless compression, Lossy compression, Discrete Cosine Transform (DCT), Principle Component Analysis (PCA), Joint photographic expert group (JPEG)

I. INTRODUCTION

Face recognition presents a challenging problem in the field of image analysis and computer vision, and it has received a great deal of attention over the last few years because of its many applications in various domains [1]. Face Recognition has its applications in different fields such as video indexing, feature extraction, law enforcement, security system, image and film processing. The face recognition system is able to identify or verify one or more persons.

Data compression is the technique, to reduce the redundancies in data representation. Data compression also helps to decrease data storage requirements and hence communication costs. Reducing the storage requirement is equivalent to increasing the capacity of the storage medium and hence communication bandwidth. The development of efficient compression techniques will continue to be a design challenge for future communication systems and advanced multimedia applications [2][3]. Data is represented as a combination of information and redundancy. Information is the portion of data that must be preserved permanently in its original form in order to correctly interpret the meaning or purpose of the data. Redundancy is that portion of data that can be removed when it is not needed or can be reinserted to interpret the data when needed. Most often, the redundancy is reinserted in order to generate the original data in its original

form. A technique to reduce the redundancy of data is defined as data compression. The redundancy in data representation is reduced such a way that, it can be subsequently reinserted to recover the original data, which is called decompression of the data. Coding process effectively reduces the total number of bits needed to represent certain information. Compression ratio is defined as the ratio of number of bits before compression to the number of bits after compression.

Need of Compression:

Image compression addresses the problem of reducing the amount of data required to represent a digital image. It is the process intended to yield a compact representation of an image, thereby reducing the image storage/transmission requirements. Compression is achieved by the removal of one or more of the following three basic data redundancies:

- Coding Redundancy
- Interpixel Redundancy
- Psycho visual Redundancy

Coding redundancy is present when less than optimal code words are used. Interpixel redundancy results from correlations between the pixels of an image. Psycho visual redundancy is due to data that is ignored by the human visual system (i.e. visually non essential information). Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies. An inverse process called decompression (decoding) is applied to the compressed data to get the reconstructed image. The objective of compression is to reduce the number of bits as much as possible, while keeping the resolution and the visual quality of the reconstructed image as close to the original image as possible.

Benefit of Compression:

- It not only reduces storage requirements but also overall execution time
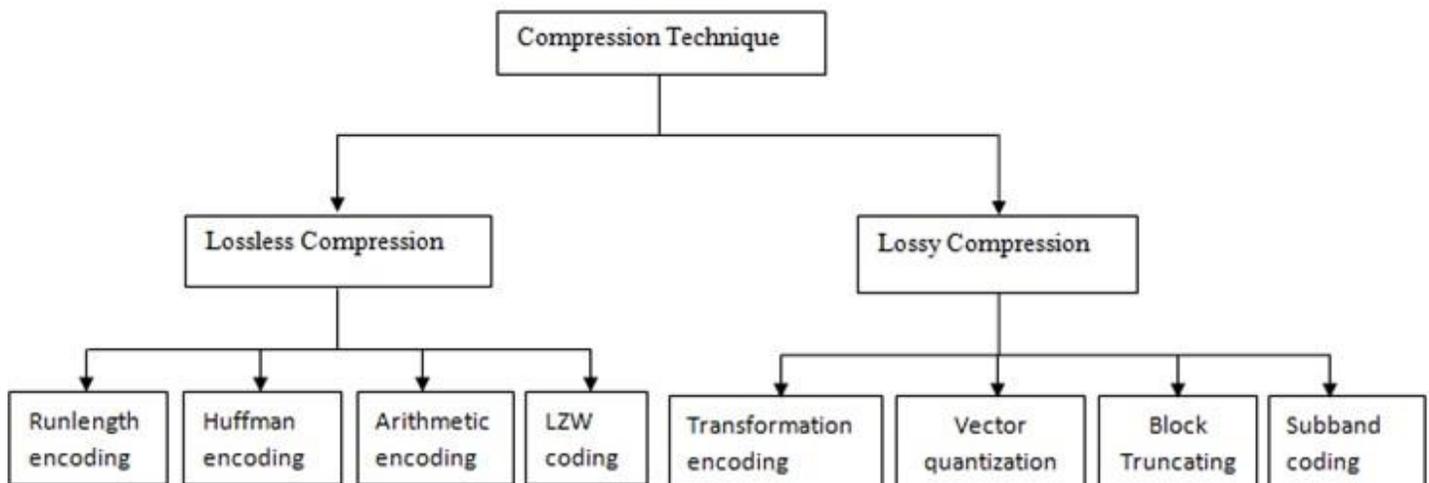

Fig 1. Classification of compression techniques

- It provides a potential cost savings associated with sending less data over switched telephone network where cost of call is really usually based upon its duration.
- It also reduces the probability of transmission errors since fewer bits are transferred.
- It also provides a level of security against illicit monitoring.

The remaining paper is structured as follows. In section 2, mostly used compression techniques for image are discussed. Brief conversation on each technique is given. In Section 3, role of DCT in case JPEG compressed domain is explored. Section 4 we discusses the principle component analysis for feature extraction. Finally, section 5 concludes the paper.

II.   COMPRESSION TECHNIQUE

The image compression techniques are mainly classified into two categories depending on whether or not an exact replica of the original image could be reconstructed using the compressed image [4][5].

In this section some of the most used image compression techniques are discussed. They are mainly classified as, a lossless compression and lossy compression [6]. The classification of compression technique is shown in the figure 1.

A.   *Lossless Compression Techniques*

In lossless compression techniques, the original image can perfectly recovered from the compressed (encoded) image. These are also called noiseless since they do not add noise to the signal (image). It is also known as entropy coding since it use decomposition techniques to eliminate/minimize redundancy.

1) *Run length Encoding:*

This is a very simple compression method used for sequential data. It is very useful in case of repetitive data. This technique replaces sequences of identical symbols (pixels), called runs by shorter symbols. The run length code for a gray scale image is represented by a sequence $\{V_i, R_i\}$ where V_i is the intensity of pixel and R_i refers to the number of consecutive pixels with the intensity V_i as shown in the example. If both V_i and R_i are represented by one byte, this span of 12 pixels is coded using eight bytes yielding a compression ratio of 1: 5.

e.g. 56,56,56,56,56,40,40,40,40,80,80

{56, 5}, {40, 4}, {80, 2}.

2) *Huffman Coding:*

This is a general technique for coding symbols based on their statistical occurrence frequencies (probabilities). The pixels in the image are treated as symbols. The symbols that occur more frequently are assigned a smaller number of bits, while the symbols that occur less frequently are assigned a relatively larger number of bits. Huffman code is a prefix code. This means that the (binary) code of any symbol is not the prefix of the code of any other symbol. Most image coding standards use lossy techniques in the earlier stages of compression and use Huffman coding as the final step.

3) *Arithmetic Coding:*

In arithmetic coding, a message is encoded as a real number in an interval from one to zero. Arithmetic coding typically has a better compression ratio than Huffman coding, as it produces a single symbol rather than several separate code words [8].   There are a few disadvantages of arithmetic coding. One is that the whole codeword must be received to start decoding the symbols, and if there is a corrupt bit in the codeword, the entire message could become corrupt. Another is that there is a limit to the precision of the number which can be encoded, thus limiting the number of symbols to encode within a codeword. The biggest drawback of the arithmetic coding is its low speed, because several needed multiplications and divisions for each symbol.

4) *LZW Coding*

LZW (Lempel- Ziv – Welch) is a dictionary based coding. Dictionary based coding can be static or dynamic. In static dictionary coding, dictionary is fixed during the encoding and decoding processes. In dynamic dictionary coding, the dictionary is updated on fly. LZW is widely used in computer industry and is implemented as compress command on UNIX.

B.   *Lossy Compression Technique*

Lossy compression is compression in which some of the information from the original message sequence is lost. This means the original sequences cannot be regenerated from the compressed sequence. Just because of information lost, it doesn't mean the quality of the output is reduced.

1)   *Transform Coding:*

In this coding scheme, transforms such as DFT (Discrete Fourier Transform) and DCT (Discrete Cosine Transform) are used to change the pixels in the original image into frequency domain coefficients (called transform coefficients). These coefficients have several desirable properties. One is the energy compaction property that results in most of the energy of the original data being concentrated in only a few of the significant transform coefficients. This is the basis of achieving the compression. Only those few significant coefficients are selected, then the remaining is discarded. The selected coefficients are considered for further quantization and entropy encoding. DCT coding has been the most common approach to transform coding. It is also adopted in the JPEG image compression standard.

2) *Vector quantization:*

The basic idea in this technique is to develop a dictionary of fixed-size vectors, called code vectors [9]. A vector is usually a block of pixel values. A given image is then partitioned into non-overlapping blocks (vectors) called image vectors. Then, for each block in the dictionary vector is determined, then its index in the dictionary is used as the encoding of the original image vector. Thus, each image is represented by a sequence of indices that can be further entropy coded.

3) *Block truncating coding:*

In this coding scheme, the image is divided into non overlapping blocks of pixels. For each block, threshold and reconstruction values are determined. The threshold is usually the mean of the pixel values in the block. Then a bitmap of the block is derived by replacing all pixels whose values are greater than or equal (less than) to the threshold by a 1 (0). Then for each segment (group of 1s and 0s) in the bitmap, the reconstruction value is determined. This is the average of the values of the corresponding pixels in the original block.

4) *Subband Coding:*

In this coding scheme, the image is analyzed to produce the components containing frequencies in well-defined bands, the sub bands. Subsequently, quantization and coding is applied to each of the bands. The advantage of this scheme is that the quantization and coding well suited for each of the sub bands can be designed separately.

III. DISCRETE COSINE TRANSFROM

The discrete cosine transform (DCT) has the property that, for the typical image, most of the visually significant information about the image is concentrated in just a few coefficients of DCT. For this reason, the DCT is often used in image compression application. The DCT is the heart of the international standard lossy image compression algorithm knows as JPEG.

DCT helps to separate the images into parts (or spectral sub-band) and each part has different importance. It transforms the signal from the spatial domain to frequency domain. DCT are important to numerous application in science and engineering from lossy compression of audio(e.g. mp3) and image (jpeg) to spectral for the numerical solution of partial differential equation.
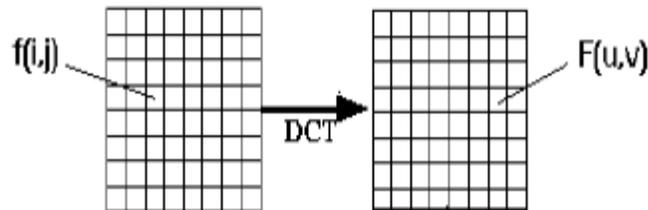

Fig. 2. DCT

In image, most of energy will concentrate in lower frequency, so if we transform an image into frequency components and throw away the higher frequency coefficient, we can reduce the amount of data needed to describe the image without losing too much image quality.

In particular, a DCT is a Fourier-related transform as that of discrete Fourier transform (DFT), but it uses only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample. There are eight standard DCT variants, of which four are common. The most common variant of discrete cosine transform is the type-II DCT, which is often called simply "the DCT", its inverse, the type-III DCT, is correspondingly often called simply "the inverse DCT" or "the IDCT". Two related transforms are the discrete sine transforms (DST), which is equivalent to a DFT of real and odd functions, and the modified discrete cosine transforms (MDCT), which is based on a DCT of *overlapping* data.

The N*N cosine transform matrix C={c (k,n)},also called the discrete cosine transform(DCT) defined as in equation (1).

$$c(k,n) = \begin{cases} \frac{1}{\sqrt{N}}, & k = 0, 0 \le n \le N-1 \\ \sqrt{\frac{2}{N}} \cos \frac{\pi (2n+1)k}{2N}, & 1 \le k \le N-1, 0 \le n < N-1 \ (1) \end{cases}$$

The one-dimensional dct of sequence {μ (n), 0≤n≤N-1} is defined as in equation (2).

$$v(k) = \alpha(k) \sum_{n=0}^{N-1} u(n) \cos\left[\frac{\pi(2n+1)k}{2N}\right] , 0 \le k \le N-1 \quad (2)$$

Where , $\alpha(0) \square \sqrt{1/N}$, $\alpha(k) \square \sqrt{2/N}$ for 1≤k≤N-1.

The inverse transformation is given by equation (3).

$$u(n) = \sum_{k=0}^{N-1} \alpha(k) v(k) \cos\left[\frac{\pi(2n+1)k}{2N}\right] , 0 \le n \le N-1 \quad (3)$$

In the JPEG image compression algorithm[10][11][12], the input is divided into 8-by-8 and two dimensional DCT is computed for each block, discard (set to zero) all 10 coefficients in each block, and then reconstruct the image using two-dimensional inverse DCT of each block.

IV. PRINCIPAL COMPONET ANALYSIS

Kirby and Sirovich were among the first to apply principal component analysis (PCA) to face images, and showed that PCA is an optimal compression scheme that minimizes the mean squared error between the original images and their reconstructions for any given level of compression. Turk and Pentland popularized the use of PCA for face recognition. Principle component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principle components [14][15].

Recognition is performed by projecting a new face image into the subspace spanned by set of face images and then classifying the face image by comparing its position in face space with position of known individual.

Principal component analysis is used to extract feature to recognize the faces. Given s-dimensional vector representation of each face image in the training set of images, PCA tends to find a t-dimensional subspace whose basis vector correspond to the maximum variance direction in the original image space [18].
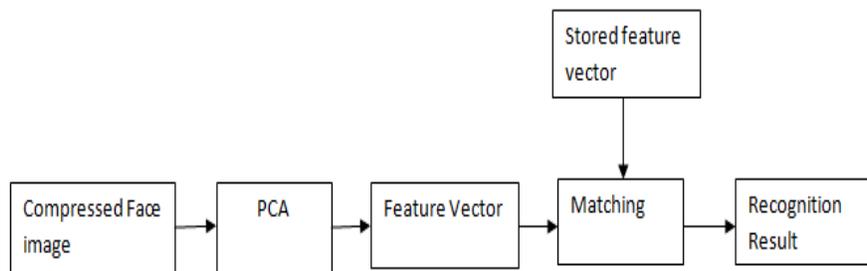

Fig. 3. Compressed Domain Face Recognition

General block diagram of the JPEG compressed domain face recognition system is shown in Fig 3. First, compressed probe images are given as input to the PCA [10][17]. Then, PCA method is applied to the selected coefficients for feature extraction in JPEG compressed domain. Finally, in the matching phase, the extracted vectors of the probe images are compared with those of the gallery images in the database which are calculated through the same process.
The following methods are generally followed in the case of PCA:

- Get some data.
- Subtract the mean.
- Calculate the covariance matrix.
- Calculate eigenvector and eigenvalues of covariance matrix.
- Choose the component and form the feature vector.
- Derive the new data set.

Let us consider a set of face images $i_1, i_2, i_3 \ldots \ldots i_m$. The average face of set is defined as in equation (4).

$$\bar{i} = \frac{1}{M} \sum_{j=1}^{M} i_j \qquad (4)$$

Each face differs from the average by vector $\phi_n = i_n - \bar{i}$.

A covariance matrix is constructed with the help of equation (5).

$$C = \frac{1}{M} \sum_{j=1}^{M} \emptyset_j \emptyset_j^T \qquad (5)$$

Then Eigen vector V_k and Eigen values λ_k, are calculated with symmetric matrix C. V_k determine the linear combination of M difference images with $\emptyset$ to form the Eigen faces b_l.

$$b_l = \sum_{k=1}^{M} V_{lk} \emptyset_k \quad, \qquad l = 1, \ldots, M \qquad (6)$$

From these Eigen faces, K (<M) Eigen faces are selected to correspond to the K highest Eigen values. A new face image I is transformed into Eigen faces component (projected into "face space") by simple operation as shown in equation (7).

$$w_{nk} = b_k(i_n - \bar{i}) \qquad (7)$$

Where, n=1,…., M and k=1,……, K.

The weights obtained from a vector $\Omega_n = \left[w_{n1}, w_{n2}, \ldots, w_{nk} \right]$ that describes the contribution of each Eigen face in representing the input face images, treating eigenfaces as basis set for face images.

V. CONCLUSION

This paper presents various types of image compression techniques and face recognition using PCA. There are basically two types of compression techniques. One is Lossless Compression and other is Lossy Compression Technique. Comparing the performance of compression technique is difficult unless identical data sets and performance measures are used. Lossy compression is most commonly used to compress multimedia data like audio, video, and still images, especially in applications such as streaming media. By contrast, lossless compression is required for text and data files, such as bank records and text articles. In many cases, it is advantageous to make a master lossless file that can then be used to produce compressed files for different purposes.

PCA is a useful technique when dealing with large datasets. PCA method is used to reduce the number of dimensions of feature space, but still to keep principle features to minimize loss of information. PCA can be derived as special case of Independent component analysis which uses Gaussian source model. PCA is appearance based method found the best performer in facial feature extraction because it keep the information of face image, rejects redundant information.

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