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Investigation of Fingerprint compression

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Abstract — *Digital images are focused to a wide variety of distortions during processing, compression, storage and reproduction any of which may cause in a dreadful condition of visual quality. Many systems use digital image compression when it is needed to transmit or store the image. JPEG, JPEG 2000, WSQ compression is the most popular image compression techniques but did not rebuild boundaries of an image perfectly. Here the new compression technique is used. Sparse method such as KSVD and SPIHT algorithm are combined which gives better result rather than the separately and K-SVD algorithm is used for dictionary creation It gives the better compression ratio.*

Keywords- *Fingerprint compression ; sparse representation; Singular Value Decomposition ; JPEG ; JPEG2000; DWT ;WSQ.*

INTRODUCTION

Recognition of images is very important such as biometric identifications. Fingerprint identification is commonly used in forensic science. Now a days large number of fingerprints are collected hence problems occurs for memory utilization hence compression techniques are used. There are many compression techniques such as JPEG, JPEG 2000, WSQ, DWT are most existing compression techniques. Among all biometric recognition techniques fingerprint recognition is very popular. In this paper combination of sparse representation techniques, it will gives better compression techniques and also PSNR.

Large number of fingerprints are collected and stored every day in a wide range of applications. In 1995, the size of the FBI fingerprint card record contained over 200 million items and record size was increasing at the rate of 30000 to 50000 new cards per day. Large volume of data consumes the amount of memory. Generally compression technology can be classified into lossless and lossy.

Lossless compression is a discussion of data compression algorithms that allows the original data to be perfectly recreated from the compressed data. By divergence, lossy compression permits reconstruction only of an approximation of the original data, though this usually increases compression rates (and therefore reduces file sizes).

Lossless compression allows the exact original images to be recreated from the compressed data. Lossless compression technologies are used in cases where it is important that the original and the decompressed data are similar. Avoiding alteration limits their compression efficiency. When used in image compression where slight distortion is acceptable, lossless compression technologies are often employed in the output coefficients of lossy compression. Lossless data compression is used in many applications such as ZIP file format and in the GNU tool gzip. Lossy compression is the type of data encoding methods that uses partial data discarding to represent the content. These techniques are used to decrease data size for storage, handling, and transmitting content.

This is opposed to lossless data compression which does not damage the image. The amount of data decline possible using lossy compression is often much higher than through lossless techniques.

Lossy compression technologies usually transform an image into another domain, quantize and encode its coefficients. During the last three decades, transform based image compression technologies have been extensively investigated. Two most common options of transformation are the Discrete Cosine Transform (DCT) and the Discrete Wavelet Transform.(DWT) Lossy compression is most commonly used to compress multimedia data (audio, video, and images), especially in applications such as streaming media and internet telephony.

The aim of this project is to implement techniques for fingerprint image enhancement and minutiae extraction. After the image enhancement construct a base matrix whose columns represent features of the fingerprint images, referring the matrix dictionary whose columns are called atoms, for a given whole fingerprint, divide it into small blocks called patches whose number of pixels are equal to the dimension of the atoms. Use the method of sparse representation to obtain the coefficients then, quantize the coefficients and encode the coefficients and other related information using lossless coding methods

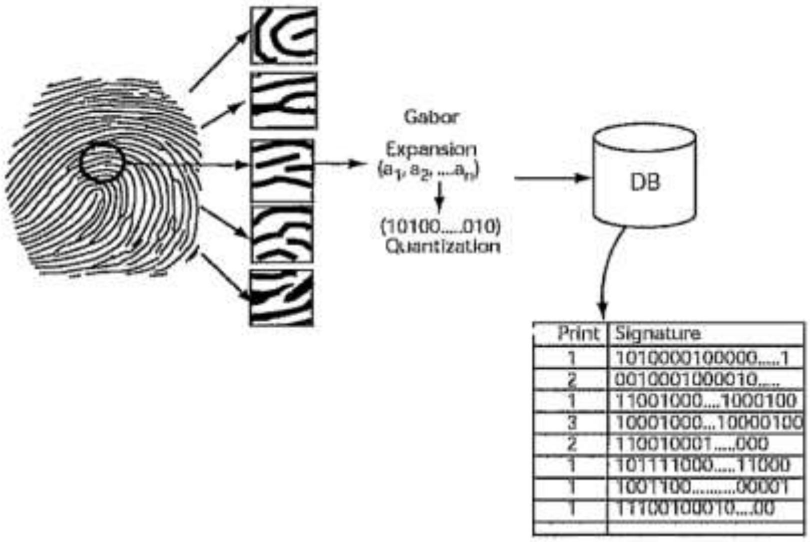


Fig 1 .Gabor determination for each patch

II LITERATURE SURVE

In last scarce years Fingerprint compression become more and more common for wallop the important data to lock the data. the primary goal of pattern recognition is supervised or unsupervised classification [1]. Among the various frameworks in which pattern recognition has been traditionally articulated. More recently, neural network techniques and methods introduced from statistical learning theory have been receiving increasing attention. The design of a recognition system needs careful attention to the following issues: definition of pattern classes, sensing environment, pattern representation, feature extraction and selection, cluster analysis, classifier design and learning, selection of training and test samples, and performance evaluation. In this field, from the last few years the general problem of recognizing complex patterns with arbitrary orientation, location, and scale remains unsolved. New and emerging applications, such as data mining, web searching, retrieval of multimedia data, face recognition, and cursive handwriting recognition, require robust and efficient pattern recognition techniques.

Due to the increasing requirements for transmission of images in computer, mobile environments [2], the research in the field of image compression has increased significantly. Image compression plays an important role in digital image processing, it is also very important for efficient transmission and storage of images. When we compute the number of bits per image resulting from typical sampling compression is needed. Therefore development of proficient techniques for image compression has become obligatory .This paper is a survey for lossy image compression using Discrete Cosine Transform, it covers JPEG compression algorithm which is used for full-colour still image applications and describes all the components of it. Image Compression addresses the problem of reducing the amount of data required to represent the digital image. We can achieve compression by removing of one or more of three basic data redundancies:

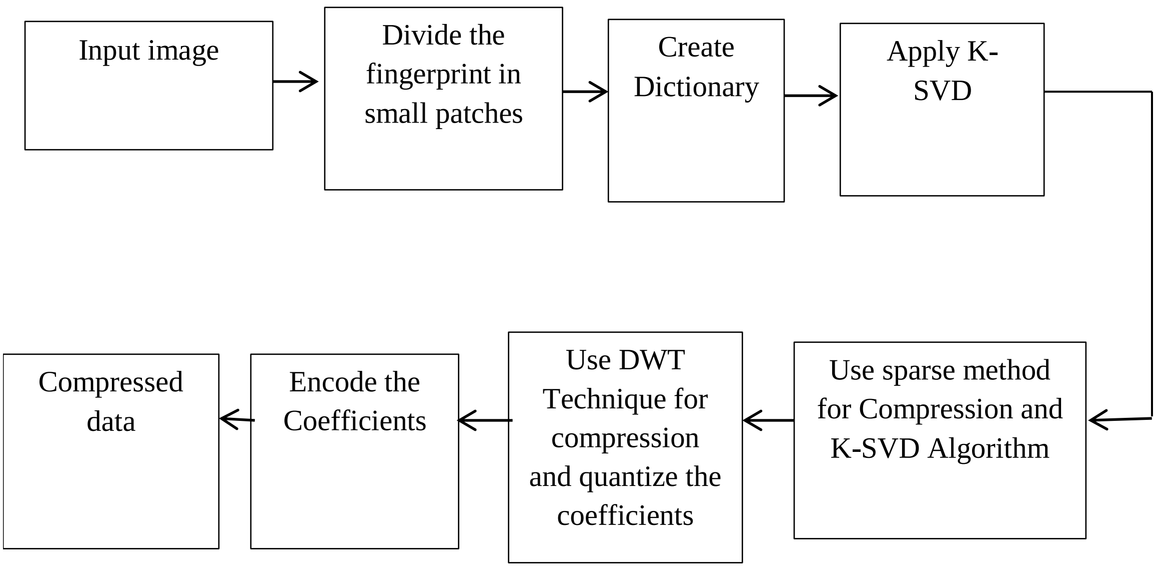
(1) Spatial Redundancy or correlation between neighboring pixels.
(2) Due to the correlation between different colour planes or spectral bands, the Spectral redundancy is founded.
(3) Due to properties of the human visual system, the Psycho-visual redundancy is founded.

We find the spatial and spectral redundancies when certain spatial and spectral patterns between
The pixels and the colour components are common to each other and the psycho-visual redundancy produces from the fact that the human eye is insensitive to certain spatial frequencies.

The time-frequency and time-scale communities have recently developed a large number of over complete waveform dictionaries—stationary wavelets, wavelet packets, cosine packets, chirp lets, and warp lets, to name a few [4]. Disintegration into over complete systems is not irreplaceable, and several methods for decomposition have been proposed, including the method of frames (MOF), matching pursuit (MP), and, for special dictionaries, the best orthogonal basis (BOB). Basis pursuit (BP) is a principle for decomposing a signal into an ―optimal‖ superposition of dictionary elements, where *optimal* means having the smallest $l1$ norm of coefficients among all such decompositions. We give examples exhibiting several advantages over MOF, MP, and BOB, including better sparsely and super resolution. BP has interesting relations to ideas in areas as assorted as ill-posed problems, abstract harmonic analysis, total variation denoising, and multiscale edge denoising. BP in highly over complete dictionaries leads to large-scale optimization problems. With signals of length 8192 and a wavelet packet dictionary, one gets an equivalent linear program of size 8192 by 212,992. Such problems can be attacked successfully only because of recent advances in linear and quadratic programming by interior-point methods. We obtain sensible success with a primal-dual logarithmic barrier method and conjugate gradient solver.

Images, captured with digital imaging sensors, transmitted through various channels, often contain noise [3]. In literature, many image restoration techniques exists for the reduction of noise from degraded image, but they usually do not succeed when applied to diversified fields degraded images with Speckle, Poisson, Gaussian and Salt & Pepper noise. In this paper, provide performance analysis of state of art image restoration techniques i.e. patch based image restoration technique for various combinations of noise and diversified field images, and also a new scheme for the removal of noise is proposed. The resulting restoration technique is shown to outperform alternative state-of-the-art restoration methods with synthetic noise to diversified field images both in terms of speed and restoration accuracy. Digital images play an important role in daily life application such as satellite television, imaging under water, magnetic resonance, computed tomography as well as in area of research and technology such as Medical, geographical information system and astronomy. Visual information is usually considered the most illustrative, informative, direct and comprehensive among all kinds of information perceived by human beings. Data sets collected by image sensors are generally contaminated by noise. Imperfect instrument, problem with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Image is greatly affected by capturing instruments, data transmission media, quantization and discrete sources of radiation. Furthermore, noise can be introduced by transmission errors and compression. Many diagnoses in Medical field are based on biomedical images derived from x–ray, computerized tomography (CT), ultra-sound, magnetic resonance imaging (MRI) and in geosciences scientists use remote sensing images to monitor planetary bodies, distant starts, and galaxies, so image must be without noise. Digital images are prone to a variety of types of noise.

III PROPOSED SYSTEM



The sparse representation methods for image compression which is shown in Fig are specifically used for fingerprint image compression; these are not efficient for
General images. The main reason for this is that general images are rich in contents thus, to obtain a dictionary with a modest size, the pre-processing is indispensable. Influenced by transformation, rotation and noise, the fingerprints of the same finger may look very different. What we first think is that each fingerprint image is realigned, independently of the

others. The most common pre-alignment technique is to translate and rotate the fingerprint according to the position of the core point. Unfortunately, reliable detection of the core is very difficult in fingerprint images with poor quality. Even if the core is correctly detected, the size of the dictionary may be overlarge because the size of a whole fingerprint image is too large. Compared with general natural images, the fingerprint images have simpler structure. They are only composed of ridges and valleys. In the local regions, they look the same. Therefore, to solve these two problems, the whole image is sliced into square and non-overlapping small patches. For these small patches, there are no problems about transformation and rotation. The size of the dictionary is not too large because the small blocks are relatively smaller. The proposed method has the ability by updating the dictionary. In this method, for a given fingerprint, slice it into small patches. For each patch its mean is calculated and subtracted from the patch. For each patch solve the minimization problem by those coefficients whose absolute value are less than a given threshold are treated as zero. Record the remaining coefficients and their locations. Encode the atom number of each patch, the mean value of each patch and the indexes, quantize and encode the coefficients. Output the compressed stream. The above algorithms have a common shortcoming, i.e., without the ability of learning, the fingerprint images can't be compressed well now. So, a novel approach based on Sparse representation is given in this paper. The proposed method has the ability by updating the Dictionary. The specific process is as follows: construct a base matrix whose columns represent features of the fingerprint images, referring the matrix dictionary whose columns are called atoms; for a given whole fingerprint, divide it into small blocks called patches whose number of Pixels are equal to the dimension of the atoms; use the method of sparse representation to obtain the coefficients; then, quantize the coefficients; last, encode the coefficients and other related information using lossless coding methods. Given a new fingerprint, slice it into square patches which have the same size with the training patches. The size of the patches has a direct impact on the compression efficiency. The algorithm becomes more efficient as the size increases. In addition, to make the patches fit the dictionary better, the mean of each patch needs to be calculated and subtracted from the patch. After that, compute the sparse representation for each patch by solving the l0 problem. Those coefficients whose absolute values are less than a given threshold are treated as zero. For each patch, four kinds of information need to be recorded. They are the mean value, the number about how many atoms to use, the coefficients and their locations. For improving algorithm ,Use Orthogonal matching pursuit instead of matching pursuit for constructing the dictionary.

$$\int_{-\infty}^{\infty} \phi(x)\,\phi(x+l)\,\mathrm{d}x = \delta_{0,l}$$

After introducing some more conditions (as the restrictions above does not produce a unique solution) we can obtain results of all these equations, i.e. the finite set of coefficients a_k that define the scaling function and also the wavelet. The wavelet is obtained from the scaling function as N where N is an even integer. The set of wavelets then forms an orthonormal basis which we use to decompose the signal. Note that usually only few of the coefficients a_k are nonzero, which simplifies the calculations.

In the following figure, some wavelet scaling functions and wavelets are plotted. The most known family of orthonormal wavelets Wavelet may be seen as a complement to classical Fourier decomposition method.

Suppose, a certain class of functions is given and we want to find 'simple functions'

$f_0, f_1, f_3, \ldots\ldots$

such that each

$$f(x) = \sum_{n=0}^{\infty} a_n f_n(x)$$

Wavelet is a mathematical tool leading to representations of the type (1) for a large
class of functions f . Wavelet theory is very new (about 25 years old) but has already proved useful in many contexts.

4.3 Proposed system (Wavelet)

A wavelet means a small wave (the sinusoids used in Fourier analysis are big waves)
and in brief, a wavelet is an oscillation that decays quickly.
Equivalent mathematical conditions for wavelet are :

$$\int_{-\infty}^{\infty} |\psi(t)|^2\, dt < \infty; \qquad (2)$$

$$\int_{-\infty}^{\infty} |\psi(t)| dt = 0; \qquad (3)$$

4.2 Wavelet Transform

Jean Morlet in 1982, introduced the idea of the wavelet transform and provided a new mathematical tool for seismic wave analysis. Morlet first considered wavelets as a family of functions constructed from translations and dilations of a single function called the "mother wavelet" ψ(t). They are defined by

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right), \quad a,b \in \mathrm{R},\ a \neq 0 \qquad (5)$$

The parameter a is the scaling parameter or scale, and it measures the degree of compression. The parameter b is the translation parameter which determines the time location of the wavelet. If |a| < 1 , then the wavelet in (5) is the compressed version (smaller support in time- domain) of the mother wavelet and corresponds mainly to higher frequencies. On the other hand, when |a| > 1, then ψa,b(t) has a larger time-width than ψ (t) and corresponds to lower frequencies. Thus, wavelets have time-widths adapted to their frequencies. This is the main reason for the success of the Morlet wavelets in signal If a function 2 f ∈ L (R), the series

$$\sum_{j \in z}\sum_{k \in Z} \langle f, \psi_{j,k} \rangle \, \psi_{j,k}(t) \qquad (6)$$

Is called the wavelet series of f and

$$\langle f, \psi_{j,k} \rangle = d_{j,k} = \int_{-\infty}^{\infty} f(t)\psi_{j,k}(t)dt \qquad (7)$$

is called the wavelet coefficients of f .

5. Signal

A signal is given as a function f which has a series representation

$$f(x) = \sum_{n=0}^{\infty} a_n x^n$$

Then all information about the function f is stored in the coefficients $\{a_n\}_{n=0}^{\infty}$

6. Classification of Signals

We can split the class of signals into two classes, namely:

1. Continuous signals
2. Discrete signals

4.5.1Discrete Wavelet Transform algorithm:

The DWT-based algorithms include three steps: a DWT computation of the normalized image, quantization of the DWT coefficients and lossless coding of the quantized coefficients. There are several other DWT-based algorithms, such as Set Partitioning in Hierarchical Trees (SPIHT) Algorithm. These algorithms are for general image compression.

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).

The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere, e.g. the dilation equation

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k)$$

Where *S* is a scaling factor (usually chosen as 2). Moreover, the area between the function must be normalized and scaling function must be orthogonal to its integer translations.

IV RESULT AND PERFORMANCE ANALYSIS

Table 1: Compressed image:

Original image size (Kb)	Compressed image (Kb)			
	SPIHT	K-SVD	Combine	DWT
88.3	47.2	5.60	4.15	4.08
100.2	46.8	7.98	6.3	4.39
108	46.3	12.5	10.6	4.13
120	46.1	14.8	11.9	4.9
142	45.8	19.7	12.3	4.91

Here the table of original image vs compressed image shown in table as we have seen result of DWT is better than others.

Table 2:PSNR

Original image size (Kb)	PSNR			
	SPIHT	K-SVD	Combine	DWT
88.3	51.78	49.45	73.04	83.073
100.2	46.5	50.2	72.6	81.0712
108	47.30	51.67	70.25	80.423
120	44.8	53.7	71.9	82.025

In this table Image size vs PSNR is shown is better than others

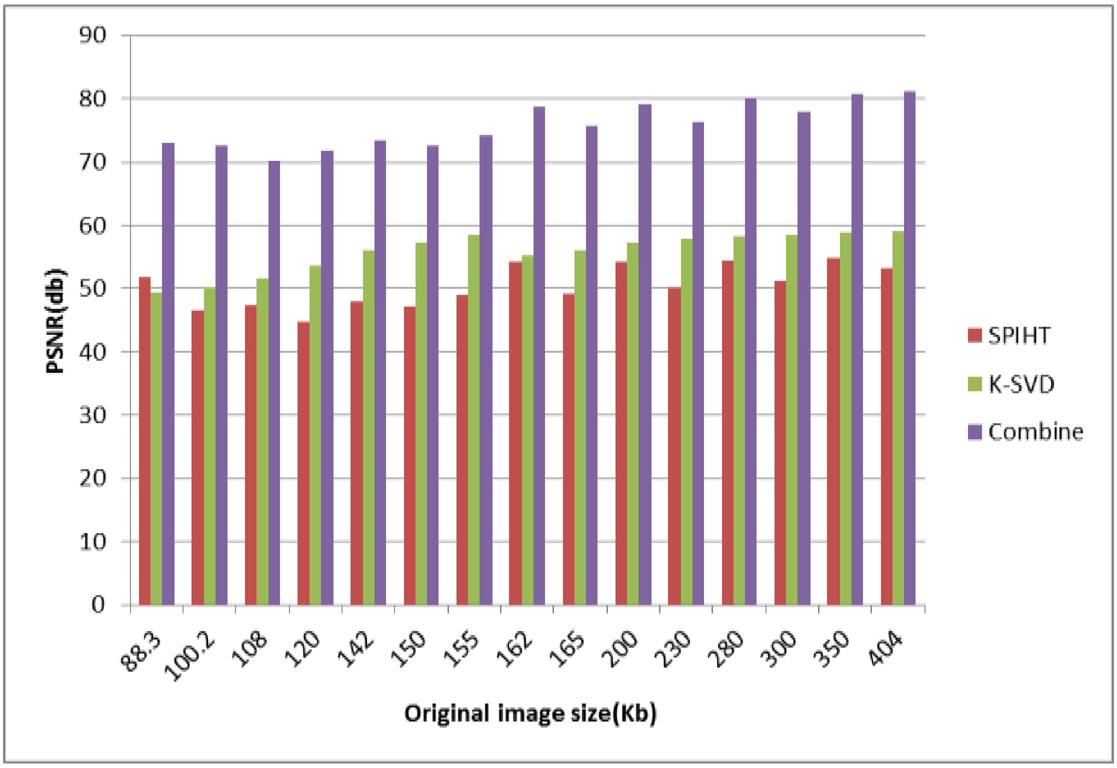
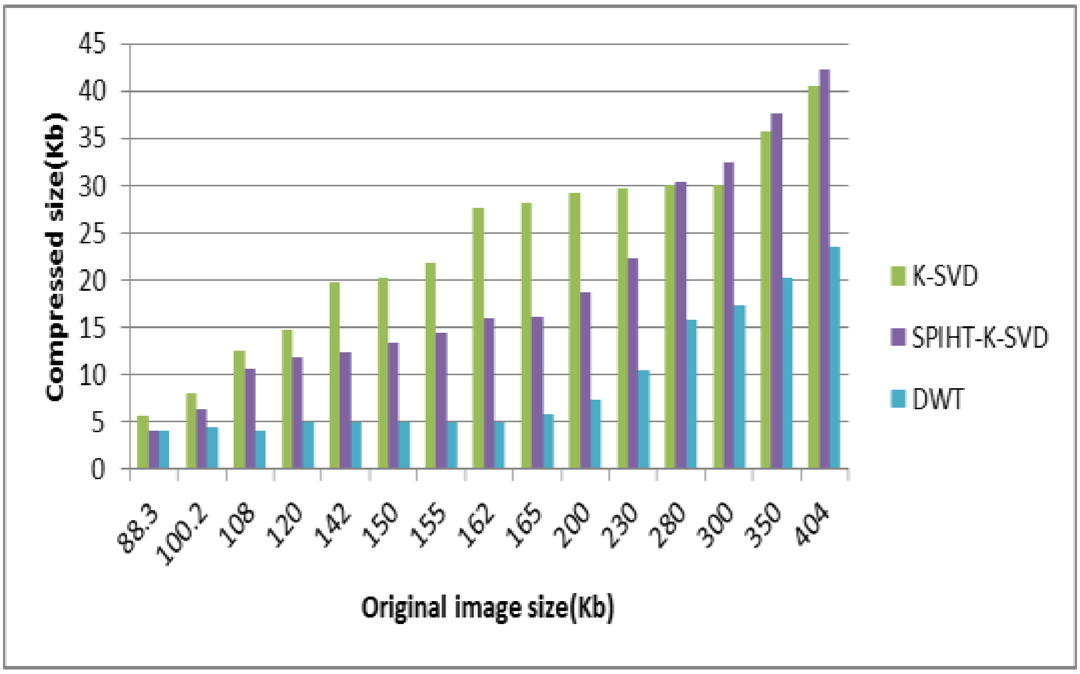


Fig 6.17. Original image size vs PSNR



V CONCLUSION

In this Dissertation, the new compression technique is implemented for compression of fingerprint images, which is DWT with sobel filter. Despite the simplicity of algorithms, it compares favorably with existing more sophisticated algorithms, especially at high compression ratios with better results that SPIHT, K-SVD, combination of SPIHT and K-SVD. This algorithm also gives higher PSNR with high compression ratio.

With this technique, It is possible to retrieve the original images with parameter with better quality.

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