

# An Optimal Sparse Encoding Assisted Robust Fingerprint Compression

R M Aparna (M TECH Student), Manoj Kumar G (Associate Professor)  
Department of Computer Science and Engineering, LBS Institute of Technology for Women, Kerala

**Abstract**— Fingerprint compression which is based on sparse representation already exists. Here by constructing a complete dictionary from a group of fingerprint patches, allows us to represent them as a sparse linear combination of dictionary atoms. Initially, construct a dictionary where fingerprint image patches that are predefined are stored. For a new given fingerprint images represent the patches according to the dictionary by computing  $l_0$ -minimisation and quantize and encode the representation. The algorithm has higher complexities due to the block by block processing mechanism which need to be taken care of. Here, we propose a method for solving sparse representation with the help of an optimization algorithm. The optimization algorithm used here is harmony search. The compression ratio, PSNR obtained by the proposed method is high compared to the one produced by existing method.

**Index Terms**— *Fingerprint, compression, sparse representation, JPEG 2000, JPEG, WSQ, PSNR.*

## 1 INTRODUCTION

Fingerprint recognition is very popular for personal identification among the many Biometric recognition technologies, due to the uniqueness, universality, collectability and invariance. Fingerprints which amount to large volume are collected and stored every day in a wide range of applications like the kind of forensics and access control. In 1995, the size of the FBI Fingerprint card archive was increasing at a very fast rate. When there is large volume of data it consumes large amount of memory. The key technique to solve the problems is finger print image compression.

To reconstruct the exact original images from the compressed data we go for Lossless compression. Used in cases where it is important that the initial and decomposed data are identical like file transfer. Avoiding distortion restricts their compression efficiency, while being used in image compression slight distortion is acceptable. Lossless compression techniques are often applied in the output coefficients of Lossy compression. Here in Lossy compression, it transforms an image into another domain, quantize and encode its coefficients. Here, some data is lost, for example in the case of video transfer.

Two common methods of transformation are Discrete Cosine Transform (DCT) [1] and Discrete Wavelet Transform (DWT) [2]. The DCT-based encoder can be thought of as compression of a stream of  $8 \times 8$  small block of images. This transform has been adopted in JPEG. JPEG has advantages such as simplicity, universality and availability. It shows bad performance at low bit-rates mainly because of the underlying block-based DCT scheme.

The Discrete Wavelet Transform (DWT) new wavelet-based compression standard for still images, namely JPEG 2000. The DWT-based algorithms include three steps: 1) a DWT computation of the normalized image 2) quantization of the DWT coefficients 3) lossless coding of the quantized coefficients. JPEG 2000 is wavelet based.

The algorithms mentioned above are for general image compression. Targeted at fingerprint images, there are some special compression algorithms. The most common one is

Wavelet Scalar Quantization (WSQ) [3],[4]. It became the FBI standard for the compression of 500dpi fingerprint images. In addition to WSQ, there are other algorithms for fingerprint compression, such as Contourlet Transform (CT) [5]. Disadvantage is that these algorithms have a common shortcoming, namely, without the ability of learning. The fingerprint images can't be compressed well now.

A novel approach based on sparse representation is given in [6]. Here a base matrix is constructed whose columns represents the features of the fingerprint images. The columns of the matrix dictionary are called atoms. The whole fingerprint is first divided into small patches whose number of pixels are equal to the dimensions of the atoms. Later, the method of sparse representation is used to represent the coefficients. Lastly, encode the coefficients and other related information using lossless coding methods. Most of the Automatic Fingerprint Identification Systems (AFIS) use minutiae (ridge endings and bifurcations) to match two fingerprint images. Here, the difference of minutiae between pre- and post compression is considered.

The shortcoming of the above method is that due to the block-by-block processing mechanism, however, the algorithm has higher complexities. The main difficulty in developing compression algorithm for fingerprint resides in the need for preserving the minutiae which are used in the matching after compression. The approach in [6] can hold most of the minutiae robustly during the compression and reconstruction.

In this paper, we propose a method where an optimization algorithm is used for solving the sparse representation. Here, the Harmony Search algorithm is used. The proposed method produces higher compression ratio and PSNR compared to the existing method. Here in this paper in the next section we will see fingerprint compression based on sparse representation in detail. Later, we will discuss the proposed method and the experimental results.

## 2 RELATED WORK

In this section we will see the fingerprint compression algorithms such as JPEG, JPEG 2000, WSQ etc: in detail.

### 2.1 JPEG:

Here in [1], its narrated that the DCT-based JPEG compression is a lossy compression method. There are 3 different kinds of errors in the compression and decompression method. The quantization error, which exists in the compression process. The main steps of JPEG compression and decompression process are shown in Figs. 1 and 2, respectively. A colour image can be broadly considered as multiple grayscale images. Without loss of generality, we suppose that the pixel values of the image in the spatial domain are shown by the integral numbers in the range [0-255]. After applying inverse DCT (IDCT) to the dequantized JPEG coefficients, the obtained float numbers need to belong to the region [0,255] in spatial domain. In order to restore the image data, the values that do not belong to [0,255] would be truncated to 0 or 255, respectively. The disadvantage of this method is the bad performance at low bit-rates mainly because of the underlying block-based DCT scheme

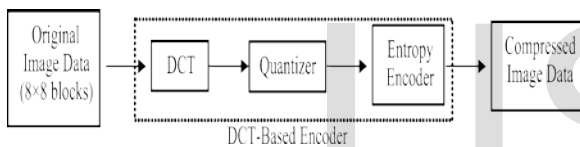


Fig 1. DCT based encoder

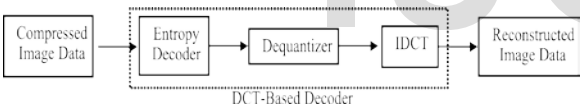


Fig 2. DCT based decoder

### 2.2 JPEG 2000

Here in [2], it is described that, goal of this method is to avoid the need for different compression standards for lossless and lossy compression.

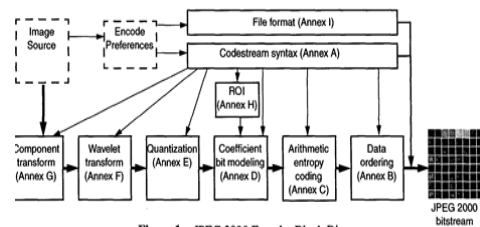


Fig 3 JPEG 2000

#### ARCHITECTURE:

**Component Transform:**The component transform provides decorrelation among image components (R, G, B). This improves the compression and allows for visually relevant quantization

**Wavelet Transform:** Two wavelet transforms possible in the standard. Both transforms provide lower resolution images and spatial decorrelation of the images to enhance compression. The 9x7 filter –produces the highest compression, 5x3 filter yields lower complexity and grants lossless compression.

**Quantization :**The trade-off between rate and distortion is acquired by quantization. Wavelet coefficients can be divided by a different value for each subband. Alternatively, portions of the coded data can be eliminated (decreasing rate and quality).

**Context Model:**This splits the bits of the quantized wavelet coefficients into groups with similar statistics so the arithmetic coder can productively compress them. Each bit plane of a coefficient is processed by one of three coding passes as narrated in Fig 3.

**Arithmetic coder :**JPEG 2000 uses the MQ binary arithmetic coder to provide lossless compression of each coding pass of quantized wavelet coefficients.

**Bitstream Ordering:**Portions of coded data (output coming from the arithmetic coder) are collected into packets. These packets have a compressed header. While the codestream syntax permits data to be accessed in almost any order, there must be some order to the data. Various orders are possible to permit progression by resolution, or quality, or location, or some combination of these.

### 2.3 WSQ

Here in [3] an overview of WSQ is given. Wsq consists of 2 parts encoding and decoding: 1) Wavelet decomposition of the initial fingerprint image 2) Quantization of wavelet coefficients 3) Lossless entropy encoding of the output of quantization. Decoding is the inverse of encoding. The quantization step has great impact on the quality of compressed images. Compression ratio around 20:1. Disadvantage: here in paper [4], the disadvantages are described. They are: 1) Wsq cannot control the compression ratio. 2) Its performance on fuzzy images is poor.

#### WSQ Decoder:

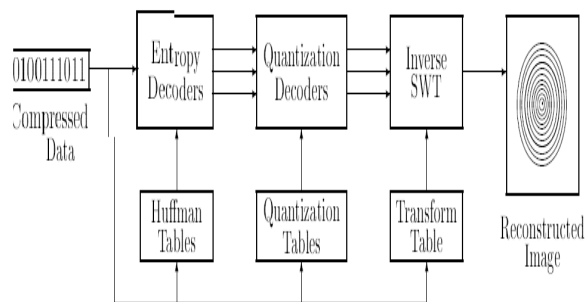


Fig 4 WSQ Decoder

### 2.4 CONTOURLET TRANSFORM

Here in [5] this is briefly described. The wavelet transform (WT) has shown its high capability to compress natural im-

ages that have smooth regions with definite boundaries. This type of transform, on the other hand, is not very useful with contours. Textured images are not acceptable for application of wavelet. Due to the mentioned shortcomings of the wavelet transform other transforms are proposed such as bandelet, curvelet, and contourlet. The contourlet transform (CT), is a geometric transform which keeps features such as contours and textures. Two main parts of the contourlet transform are Laplacian pyramid (LP) and directional filter bank (DFB). This transform has a redundancy ratio of less than  $4/3$ . In NLA algorithms after executing an orthogonal transform of the image,  $m$  larger coefficients are stored and the rest of the coefficients are eliminated. The reconstructed image will be an approximation of the original one and is formed using the  $M$  stored coefficients.

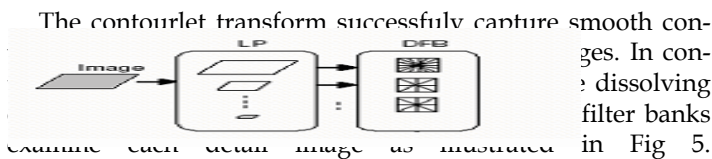


Fig 5. A flowgraph of the contourlet transform

5. A flowgraph of the contourlet transform

### 3 FINGERPRINT COMPRESSION BASED ON SPARSE REPRESENTATION

Here, in this section the details of Fingerprint Compression based on Sparse Representation [6] is discussed. The algorithm is given below.

**Algorithm 1** Fingerprint Compression Technique based on Sparse Representation [6].

- 1: For a given fingerprint, slice it into small Patches.
- 2: For each patch, its mean is calculated and subtracted from the patch.
- 3: For each patch, solve the  $l_0$  - minimization problem by MP method.
- 4: Those coefficients whose absolute value is less than a given threshold are treated as zero. Record the remaining coefficients and their locations.
- 5: Encode the atom number of each patch, the mean value of each patch, and the indexes; quantize and encode the coefficients.
- 6: Output the compressed stream.

When compared to natural images fingerprint images have simpler structure. Fingerprint images are composed of ridges and valleys. In the local regions they look the same. We need to

obtain a dictionary whose size is modest. In order to obtain that the preprocessing is indispensable. Usually the fingerprint is translated and rotated according to the core point. This is a common pre-alignment technique that is used. The problem is that reliable detection of core is difficult in fingerprint images with poor quality. Therefore, to solve these two problems, the whole image is sliced into square and non overlapping patches. The problems about transformation and rotation are solved due to this. Due to the small blocks the size of the dictionary is not too large.

#### A. Construction of the Dictionary

Dictionary will be constructed in 3 ways. The first method: choose fingerprint patches from the samples that are trained at random and arrange these patches as columns of the dictionary matrix. The second method: in generic, patches from foreground of a fingerprint have a position while the patches from the background don't have, this fact can be used to make a dictionary. Divide the interval  $[00, \dots, 1800]$  into equal-size intervals. Here each interval is represented by an position (the middle value of each interval is chosen).

#### B. Compression of a Given Fingerprint

The algorithm becomes more efficient as the size of patch increases. However, the complexity of computation and the size of the dictionary also increase rapidly to make the patches fit the dictionary better, the average of each patch needs to be calculated and subtracted from the patch.

#### C Coding and Quantization

Entropy coding of the atom number of each patch, the mean value of each patch, the coefficients and the indexes is carried out by static arithmetic coders. The quantization of coefficients is performed using the Lloyd algorithm.

#### D Analysis of the Algorithm Complexity

The algorithm has two parts, namely, the training process and the compression process. Training process is off-line, so only the complexity of compression process is analyzed. Size of the patch is  $m \times n$ , number of patches in the dictionary is  $N$ , the total number of scalar multiplications for compressing a fingerprint image is  $(M1 \times N1 / m \times n) \times LmnN$ , namely,  $LM1N1N$ .

### 4 PROPOSED METHOD

Here, in this paper we propose a method to solve sparse representation using an optimization algorithm. Here, the algorithm used is Harmony search. Initially, we find region of interest and then perform histogram equalization. Later image is being divided into patches. Shortly, after this using harmony search along with the existing method we are able to obtain a higher compression ratio and PSNR compared to the existing method. Now we will discuss about harmony search in detail:

**4.1 Basic Harmony Search Algorithm:**

The music improvisation is a process of searching for the better harmony by trying various combinations of pitches that should follow any of the following three rules [9]:

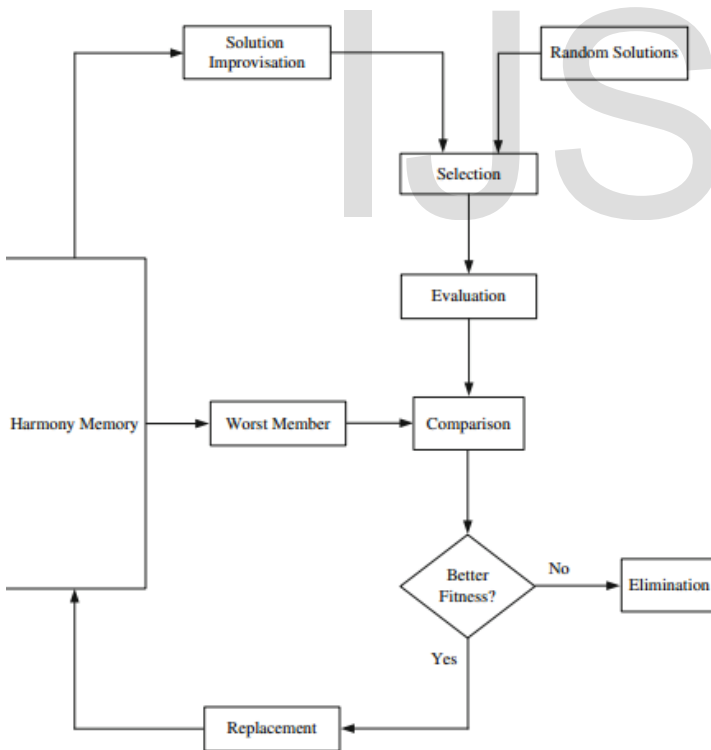
1. playing any one pitch from the memory
2. playing an adjacent pitch of one pitch from the memory
3. playing a random pitch from the possible range.

This process is mimicked in each variable selection of the HS algorithm. Similarly, it should follow any of the three rules below:

1. choosing any value from the HS memory;
2. choosing an adjacent value from the HS memory;
3. choosing a random value from the possible value range.

The three rules in the HS algorithm are effectively directed using two important parameters: harmony memory considering rate (HMCR) and pitch adjusting rate (PAR). Fig 6 shows the flowchart of the basic HS method.

Fig 6. Harmony Search (HS) method



Step 1. Initialize the HS memory (HM). The initial HM consists of a given number of randomly produced solutions to the optimization problems under consideration. For an n-dimension problem, an HM with the size of HMS can be represented as in fig 7.

Fig 7. HMS representation

$$HM = \begin{bmatrix} x_1^1, x_2^1, \dots, x_n^1 \\ x_1^2, x_2^2, \dots, x_n^2 \\ \vdots \\ x_1^{HMS}, x_2^{HMS}, \dots, x_n^{HMS} \end{bmatrix},$$

where  $[x_1^i, x_2^i, \dots, x_n^i]$  ( $i = 1, 2, \dots, HMS$ ) is a solution

HMS is typically set to be between 50 and 100.

Step 2. Improvise a new solution  $[x_1^i; x_2^i; \dots; x_n^i]$  from the HM. Each component of this solution,  $x_j^i$ , is obtained based on the HMCR. The HMCR is defined as the probability of selecting a component from the present HM members, and  $1-HMCR$  is, therefore, the probability of producing it randomly. If  $x_j^i$  comes from the HM, it is chosen from the  $j$ th dimension of a random HM member, and it can be further changed according to the PAR. The PAR determines the probability of a candidate from the HM to be mutated. Obviously, the extemporization of  $x_1^i; x_2^i; \dots; x_n^i$  is rather similar to the production of the offspring in the genetic algorithm (GA) [7],[8] with the mutation and crossover operations. However, the GA creates fresh chromosomes using only one (mutation) or two (simple crossover) existing ones, while the creation of new solutions in the HS method utilizes all of the HM members.

Step 3. Update the HM. The new solution from Step 2 is evaluated. If it yields a better fitness than that of the worst member in the HM, it will replace that one. Otherwise, it is eliminated.

Step 4. Repeat Step 2 to Step 3 until a preset termination criterion, e.g., the maximal number of iterations, has been met.

Apparently, the HMCR and PAR are two fundamental parameters in the HS algorithm, which control the component of solutions and even impact convergence speed. The former is used to set the probability of using the historic information stored in the HM. For example, 0.9 implies that each component of a new solution will be chosen from the HM with 90 % probability, and 10 % probability from the entire feasible range. Each component of the solution is subject to whether it should be pitch-adjusted, which is determined using PAR.  $1-PAR$  means the rate of doing nothing. For example, a PAR of 0.3 implies that the neighboring value will be chosen with 30 % probability.

**5 RESULTS AND DISCUSSION**

Initially, we find the region of interest in the input image then perform histogram equalization. Later, the image is being divided into patches and compressed using sparse representa-

tion. The dictionary is updated by K-SVD algorithm. In sparse we compute the coefficient matrix using matching pursuit. In the proposed method we have used harmony search algorithm to solve sparse representation. The results are being compared. Here, we can see that the proposed method produces higher compression and PSNR compared to the existing one using sparse representation. This is shown in fig 8 and fig 9.

Fig 8. Comparison of Compression Ratio.

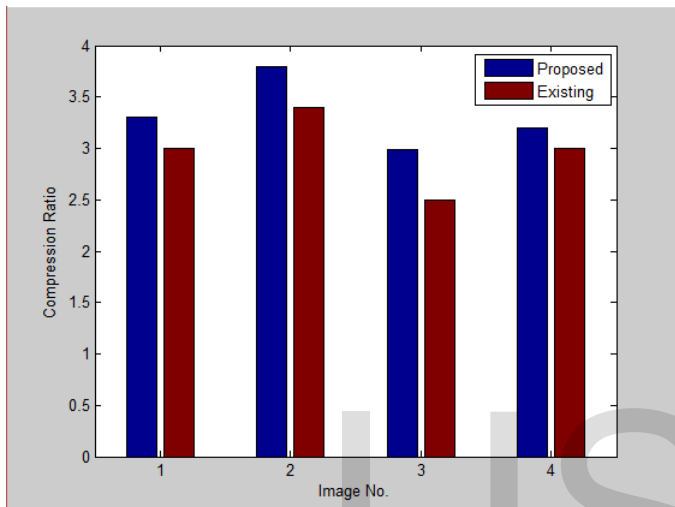


Fig 9. Comparison of PSNR.

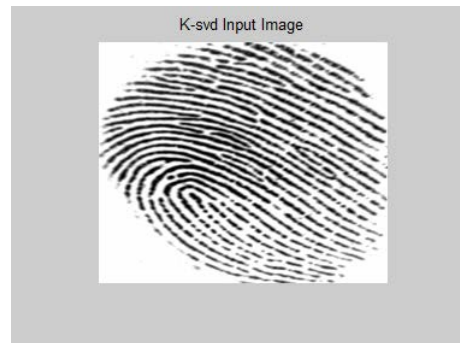
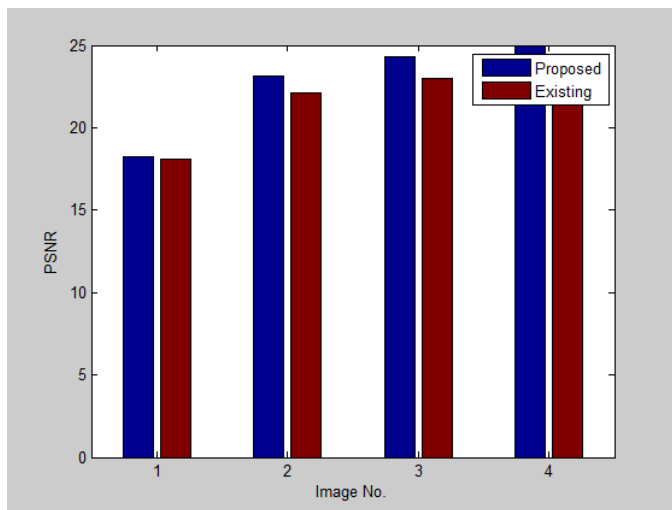


Fig 10. Input image

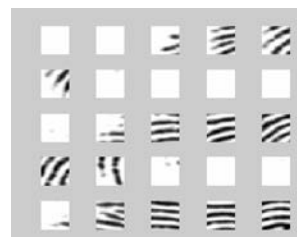


Fig 11. Image divided into patches



Fig 12. Compressed image using sparse representation

Here fig 10 shows the input image where histogram equalization has been applied. Fig 11 shows the image divided into patches. Compressed image using sparse representation is shown in fig 12.

## 6 CONCLUSION

Here in this paper different fingerprint compression methods are discussed. The fingerprint compression based on Sparse Representation is efficient than rival compression techniques like JPEG, JPEG 2000, WSQ, CT etc, especially at high compression ratio and can hold most of the minutiae powerfully during the compression phase and reconstruction phase. However, the algorithm has higher complexities due to the presence of block-by-block processing mechanism. Our proposed method uses an optimization algorithm to resolve sparse representation. The algorithm used is harmony search algorithm. This proposed method produces higher compression ratio and PSNR compared to existing method. The future work can be based on including new features and methods for constructing dictionary. We could provide training samples which include different quality ('good', 'bad', 'ugly'). These possibili-

ties can be thought of.

## ACKNOWLEDGMENT

We are greatly indebted to our principal Dr. K. C. RAVEEN-DRANATHAN, Dr. SHREELEKSHMI R., Professor, Head of the Department of Computer Science and Engineering, LBS Institute of Technology for Women who has been instrumental in keeping our confidence level high and for being supportive in the successful completion of this paper. We would also extend our heartfelt gratitude to all the staff members in the Department; also would like to thank all our friends and well-wishers who greatly helped in our endeavor. Above all, we thank the Almighty God for the support, guidance and blessings bestowed on us, which made it a success.

## REFERENCES

- [1] Detecting Double JPEG Compression With the Same Quantization Matrix Fangjun Huang, Member, IEEE, Jiwu Huang, Senior Member, IEEE, and Yun Qing Shi, Fellow, IEEE[2010]. W.-K. Chen, *Linear Networks and Systems*. Belmont, Calif.: Wadsworth, pp. 123-135, 1993. (Book style)
- [2] JPEG 2000: Overview, Architecture, and Applications Michael J. Gormish, Daniel Lee, Michael W. Marcellin[2000].
- [3] FBI wavelet / scalar quantization standard for greyscale finger print image compression, Jonathan Bradley, Christopher M Brislawn[1993].
- [4] An improved WSQ Finger print image compression algorithm, Jinshang Tang[2008]
- [5] Fingerprint Compression Using Contourlet Transform and Multistage Vector Quantization, S. Esakkirajan, T. Veerakumar, V. Senthil Murugan and R. Sudhakar [2006]
- [6] Fingerprint Compression Based on Sparse Representation Guangqi Shao, Yanping Wu, Yong A, Xiao Liu, and Tiande Guo[2014].
- [7] R. Poli, W.B. Langdon, *Foundations of Genetic Programming* (Springer, Berlin, 2002).
- [8] M. Krug, S.K. Nguang, J. Wu et al., GA-based model predictive control of boiler-turbine systems. *Int. J. Innov. Comput. Inf. Control* 6(11), 5237-5248 (2010)
- [9] Z.W. Geem, J.H. Kim, G.V. Loganathan, A new heuristic optimization algorithm: harmony search. *Simulation* 76(2), 60-68 (2001).