

# FINGERPRINT COMPRESSION BASED ON SPARSE REPRESENTATION

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**Abstract** A new finger print compression algorithm based on sparse representation is used. Obtaining an over complete dictionary from a set of finger print patches allows us to represent them as a sparse linear combination of dictionary atoms. In the algorithm, we first construct a dictionary for predefined finger print image patches. For a new given finger print image, represent its patches according to the dictionary by computing  $l^0$ -minimization and then quantize and encode. Here, we consider the effect of various factors on compression results. Three groups of finger print images are tested. The experiments demonstrate that our algorithm is efficient compared with several competing compression techniques (JPEG, JPEG 2000, and WSQ), especially at high compression ratios. The experiments also illustrate that the proposed algorithm is robust to extract minutiae.

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**Index Term:** -finger print, compression, sparse matrix's, quantize

## I Introduction

Recognition of persons by means of biometric characteristics is an important technology in the society, because biometric identifiers can't be shared and they intrinsically represent the individual's bodily identity. Among many biometric recognition technologies, finger print recognition is very popular for personal identification due to the uniqueness, universality, collectability and invariance. Large volumes of finger print are collected and stored every day in a wide range of applications, including forensics and access control.

In 1995, the size of the FBI fingerprint card archive contained over 200 million items and archive size was increasing at the rate of 30,000 to 50,000 new cards per day. Large volumes of data consume the amount of memory. Finger print image compression is a key technique to solve the problem.

Generally, compression technologies can be classified into lossless and lossy. Lossless compression allows the exact original images to be reconstructed from the compressed data. Lossless compression technologies are used in cases where it is important that the original and the decompressed

data are identical. Avoiding distortion 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. 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 researched and some standards have appeared. Two most common options of transformation are the Discrete Cosine Transform (DCT) and the Discrete Wavelet Transform (DWT). 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. The JPEG compression scheme has many advantages such as simplicity, universality and availability. However, it has a bad performance at low bit-rates mainly because of the underlying block-based DCT scheme.

For this reason, as early as 1995, the JPEG-committee began to develop a new wavelet-based compression standard for still images, namely JPEG 2000. 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. Compared with JPEG, JPEG 2000 provides many features that support scalable and interactive access to large-sized image. It also allows extraction of different resolutions, pixel fidelities, regions of interest, components and etc.

There are several other DWT-based algorithms, such as Set Partitioning in Hierarchical Trees (SPIHT) Algorithm. The above algorithms are for general image compression. Targeted at fingerprint images, there are special compression algorithms. The most common is Wavelet Scalar Quantization (WSQ). It became the FBI standard for the compression of 500 dpi finger print images.

Inspired by the WSQ algorithm, a few wavelet packet based finger print compression schemes have been developed. In addition to WSQ, there are other algorithms for finger print compression, such as Contour let Transform (CT). These algorithms have a common shortcoming, namely, without the ability of learning. The finger print images can't be compressed well now. They will not be compressed well later. Here, a novel approach based on sparse representation is given. The proposed method has the ability by updating the dictionary.

## 2 Literature survey

### 2.1 A new, fast, and efficient image codec based on set partitioning in hierarchical trees

**Authors: A. Said and W. A. Pearlman**

**Abstract:** Embedded zero tree wavelet (EZW) coding, introduced by Shapiro in 1993, is a very effective and computationally simple technique for image compression. We offer an alternative explanation of the principles of its operation, so that the reasons for its excellent performance can be better understood. These principles are partial ordering by magnitude with a set partitioning sorting algorithm, ordered bit plane transmission, and exploitation of self-similarity across different scales of an image wavelet transform. Moreover, we present a new and different implementation based on

set partitioning in hierarchical trees (SPIHT), which provides even better performance than our previously reported extension of EZW that surpassed the performance of the original EZW. The image coding results, calculated from actual file sizes and images reconstructed by the decoding algorithm, are either comparable to or surpass previous results obtained through much more sophisticated and computationally complex methods. In addition, the new coding and decoding procedures are extremely fast, and they can be made even faster, with only small loss in performance, by omitting entropy coding of the bit stream by the arithmetic code.

### 2.2 Finger print compression using contour let transform with modified SPIHT algorithm

**Authors: R. Sudhakar, R. Karthiga, and S. Jayaraman.**

**Abstract:** Large volumes of finger prints are collected and stored every day in a wide range of applications, including forensics, access control etc., and is evident from the database of Federal Bureau of Investigation (FBI), which contains more than 70 million finger prints. Wavelet based Algorithms for image compression are the most successful, which result in high compression ratios is compared to other compression techniques. Even though wavelet bases are providing good compression ratios, they are not optimal for representing images consisting of different regions of smoothly varying grey-values, separated by smooth boundaries.

This issue is addressed by the directional transforms, known as contour lets which have the property of preserving edges. This project focuses mainly on the new finger print compression using contour let transform (CT), which includes elaborated repositioning algorithm for the CT coefficients, and Modified set partitioning in hierarchical trees (SPIHT) which is applied to get better quality, i.e., high peak signal to noise ratio (PSNR). The results obtained are tabulated and compared with those of the wavelet based ones

### 2.3 Robust face recognition via sparse representation

**Authors: J. Wright, A. Y. Yang, A. Ganesh, S. S.**

## Sastry, and Y. Ma

**Abstract:** We consider the problem of automatically recognizing human faces from frontal views with varying expression and illumination, as well as occlusion and disguise. We cast the recognition problem as one of classifying among multiple linear regression models and argue that new theory from sparse signal representation offers the key to addressing this problem. Based on a sparse representation computed by  $C^1$ -minimization, we propose a general classification algorithm for (image-based) object recognition. This new framework provides new insights into two crucial issues in face recognition: feature extraction and robustness.

For feature extraction, we show that if sparsity in the recognition problem is properly harnessed, the choice of features is no longer critical. What is critical, however, is whether the number of features is sufficiently large and whether the sparse representation is correctly computed. Unconventional features such as downsampled images and random projections perform just as well as conventional features such as eigenfaces and Laplacianfaces, as long as the dimension of the feature space surpasses certain threshold, predicted by the theory of sparse representation. This framework can handle errors due to occlusion and corruption uniformly by exploiting the fact that these errors are often sparse with respect to the standard (pixel) basis. The theory of sparse representation helps predict how much occlusion the recognition algorithm can handle and how to choose the training images to maximize robustness to occlusion. We conduct extensive experiments on publicly available databases to verify the efficiency of the proposed algorithm and corroborate the above claims.

### 3. Implementation Study

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 researched and some standards have appeared. Two most common

options of transformation are the Discrete Cosine Transform (DCT) and the Discrete Wavelet Transform (DWT).

### DISADVANTAGES OF EXISTING SYSTEM:

The existing systems techniques have a common shortcoming, namely, without the ability of learning. The fingerprint images can't be compressed well now.

### 3.1 proposed methodology

- In this paper, a novel approach based on sparse representation is given. 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.
  - We will take it into consideration. In most Automatic Fingerprint identification System (AFIS), the main feature used to match two fingerprint images are minutiae (ridges endings and bifurcations). Therefore, the difference of the minutiae between re- and post-compression is considered in the paper.
- ADVANTAGES OF PROPOSED SYSTEM:
- A new compression algorithm adapted to fingerprint images is introduced. Despite the simplicity of our proposed algorithms, they compare favorably with existing more sophisticated algorithms, especially at high compression ratios. Due to the block-by-block processing mechanism, however, the algorithm has higher complexities.
  - The experiments show that the block effect of our algorithm is less serious than that of JPEG.

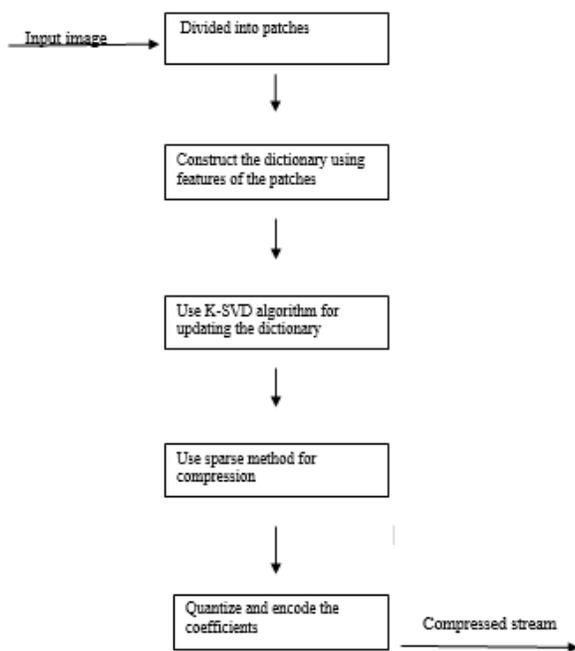


Fig 1: proposed model

### 3.2 Methodology

#### 3.2.1 Upload Image:-

In this module we are uploading the finger print image, which is to be compressed. Here, we have taken only the images with PNG (Portable Network Graphics) image type only. Other type of images like (JPEG, GIF, BMP, ETC) can also be used.

#### 3.2.2 Compress Image using SVD:-

In this module the uploaded PNG image is compressed to the maximum extend. The original image is applied with K-SVD (K- Singular Value Decomposition) algorithm and it is also tested for data loss during compression. Our approach is taken such that the image compression is lossless and the compressed image will be stored.

#### 3.2.3 Comparison Graph:-

Here the original image and the generated compressed image sizes are compared and the comparison is shown by using bar graph and it is observed that the compression is maximum.

#### 3.2.4 K-SVD ALGORITHM:

K-SVD is an iterative method that alternates between sparse coding of the examples based on the current dictionary and a process of updating the dictionary atoms to better fit the data. The update of the dictionary columns is combined with an update of the sparse representations, there by accelerating convergence.

#### 3.2.5 Close Application:-

Here we are going to terminate the application.

### 4 Results and Evolution Metrics

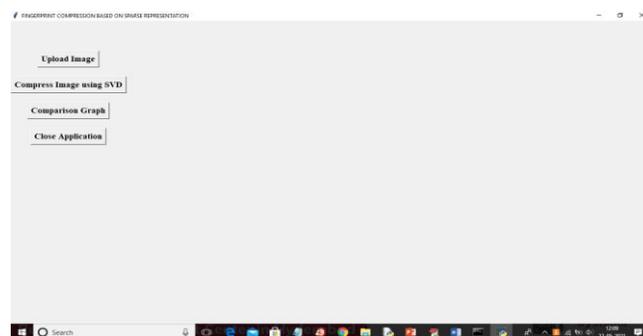


Fig2:- home page

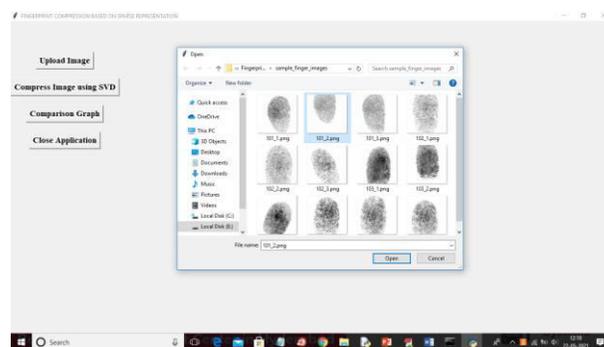
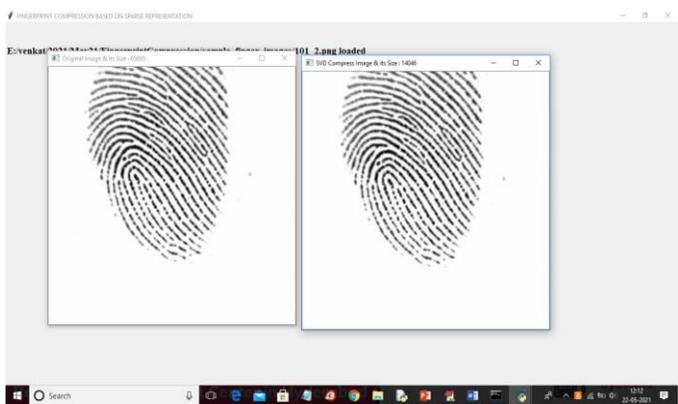
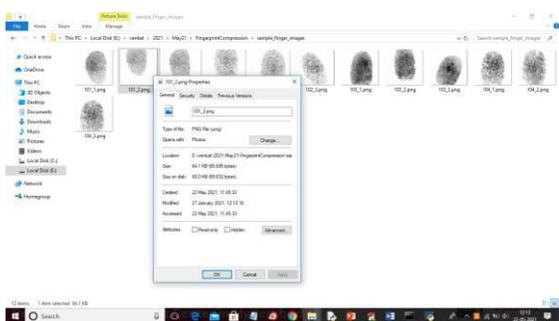


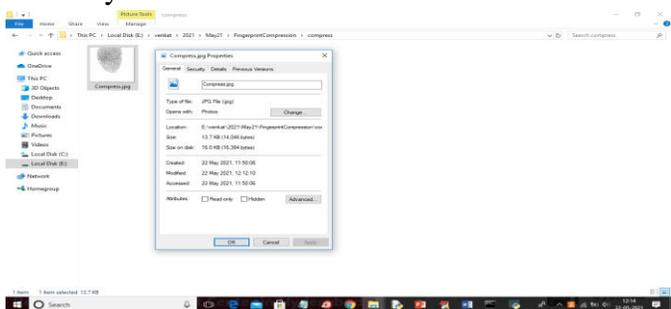
Fig 3 upload the image



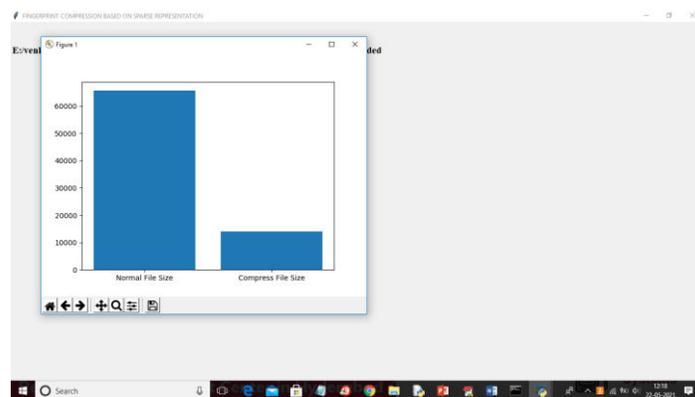
**Fig 4: - image compression**



**Fig 5:-** In above screen first image is the original image and in the title bar of image you can see their size in bytes where original image having size as 65695 bytes and SVD compress image size is 14046 bytes and the same size you can see in below image directory.



**Fig 6:-**In above screen for 101\_2.png the image size is 64.1 KB and see the same image size in compress folder after compression.



**Fig 7:-** In above graph x-axis represents technique name and y-axis represents image size and in above screen we can see after compression images size is reduced.

### 5 Conclusion

A new compression algorithm adapted to fingerprint images is introduced. Despite the simplicity of our proposed algorithms, they compare favorably with existing more sophisticated algorithms, especially at high compression ratios. Due to the block-by-block processing mechanism, however, the algorithm has higher complexities. The experiments show that the block effect of our algorithm is less serious than that of JPEG. We consider the effect of three different dictionaries on fingerprint compression. The experiments reflect that the dictionary obtained by the K-SVD algorithm works best. Moreover, the larger the number of the training set is, the better the compression result is. One of the main difficulties in developing compression algorithms for fingerprints resides in

the need for preserving the minutiae which are used in the identification. The experiments show that our algorithm can hold most of the minutiae robustly during the compression and reconstruction.

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