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Efficient Low Bit Rate Image Coder for Fingerprint Image Compression

V. REKHA[1] AND V. KAVITHA[2]
[1]*Department of Computer Science*
Ponjesly College of Engineering
Anna University
Chennai, 600025 India
[2]*Department of Computer Science*
University College of Engineering
Tamil Nadu, 631552 India
E-mail: rekha_anu2003@yahoo.co.in; kavinayav@gmail.com

Automatic fingerprint recognition is an on-demand system in most of the authentication devices. The security system only has limited memory space due to the expensive nature of memory elements. However, as more persons are included in the repository, the size of the database has grown extensively. So the memory storage is a challenging problem while storing high quality or too many images. This paper proposes a Pattern Optimization from Subset Tree (POST) image coder for fingerprint image compression which improves the coding efficiency. Initially, extract the ridge based features after the median filter smoothing for the fingerprint identification system. The features thus formed as a probability map and further processed for compression. POST identifies the significant coefficients from the subdivided tree coefficients and the resultant stream of bit patterns are optimized for low bit rate. Finally, the experimental results demonstrate the performance measures in terms PSNR, CR, bpp, and EER for the compression scheme.

Keywords: compression, feature extraction, fingerprint, image coder, optimization

1. INTRODUCTION

More than the years passed, the fingerprint is used for solving crimes, and investigations etc [1], but it needs training procedures with varied qualities, increase workload, high demand *etc*. These make it time-intensive, slow and decreased efficiency. Furthermore, nowadays the fingerprint method is being improvised to increase the efficiency of manual fingerprint recognition by the Automatic Fingerprint Identification (AFIS) [2]. According to the law enforcement agencies, an AFIS system is introduced for the fingerprint recognition technology more recently. The physical characteristics of a person are identified using biometric technology. The various biometric characteristics are fingerprints, face, voice, and signature *etc*. [3]. This characteristic has an authentication in the computer-based security system. The ID cards, punch card, secret PIN, and password are used for identification system but it also has some limitations, such as stolen cards, hacking *etc*. But, these limitations can be overcome by biometric identification and possess additional security.

The most efficient, effective and successful applications for identification and investigation is fingerprint identification. The most important detail in the fingerprint is the

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ridges and it may be present in the upper skin layer [4]. Thereby, the fingerprint can be modified. When the huge fingerprint image is taken, memory storage is a problematic one. Each finger impression has 768×768 pixels at 256 gray levels, and compressed fingerprint has 589, 824 bytes and with 10Mb totally. In identification, if the person's fingerprint image increases, then the size of the database will also increase. So, it is necessary to store high-quality fingerprint images in low bit rate [5]. The management of data is a critical issue in fingerprint identification. So, an effective compression method is needed to increase the database storage and reduce the size of the fingerprint images without reducing the quality of the images [6, 7].

Lossy and lossless are the two types of commonly used compression. The lossless compression is used for medical imagining, technical drawing, clip art etc, where the lossy compression is used for the natural image compression and for the low bit rate. The JPEG, PNG AND GIF, TIFF are considered as lossless compression; where DCT [8], JPEG [9], JPEG 2000 [10], wavelet transform [11], Dj Vu [12] are considered as lossy compression. Mostly, lossy compression scheme is used in the finger print verification system but preserves the most important information.

The image compression contains both encoder and decoder sections, whereas in encoder, the original image is encoded, and in the decoder, the encoded image can be decoded and given as original image [13]. Considering 8×8 pixel images for the compression method, first, the image is processed by transformation function. Discrete Cosine Transform (DCT) [14], Discrete Fourier Transform (DFT), and Discrete Wavelet Transform (DWT) [15] are some of the transform functions that convert spatial domain to discrete domain. The fingerprint image compression can be done by various technologies such as JPEG [16], JPEG 2000 [17], WSQ [18], K-SVD [19] and SAM [20]. Although numerous compression schemes were introduced previously, it lacks in the low bit rate compression for high quality finger print images.

The overall structure of the paper is structured as follows: The recent related works are related to fingerprint image compression is given in section 2. Section 3 describes the detailed description about a proposed POST coder for image compression. Section 4 defines the result and evaluation of the proposed work. Finally, the paper is concluded with a conclusion that it provides better compression ratio with the proposed approach.

2. RELATED WORK

The fingerprint identification by biometric characteristics is an important technology in the present era. Among various biometric identifications, a fingerprint is one of the important biometric identification, large biometric information is collected and stored every day, so it needs a desired amount of storage space. For the efficient use of identification and storing biometric information, the compression method is introduced. Some of the related papers and their proposed work of fingerprint compression are given below.

Grailu *et al.* [21] proposed a compression scheme in SPC with local SNR. The problem causes the verification performance and cannot be extracted from low-bit-rate-compressed fingerprint images. The main problem occurred was contrast variation within the original image. This paper deals with applications of fingerprint image compression in high compression ratio for preserving and improving the performance of verification in the compressed image. The SPC coder without the SPC algorithm can also be utilized for compression methods. The new system improves the ridge-valley quality and verification performance of compressed fingerprint images. Although, the compression performance was not improved with the average PSNR, erasures *etc*., some drawbacks occur in this method.

Bille *et al.* [22] proposed the Karp-Rabin fingerprinting and most widely used for compression of images to strings. The main idea used to map the substrings by considering a sequence characters as a digit of integer is base σ. Where σ is the polynomial universe. Then the fingerprint images of the sting have a constant size by considering the hash value and collision-free with a high probability of hash function. The main problem occurred is the classic string matching problem. To solve this problem, Karp and Rabin fingerprinting are used. The Karp-Rabin represents i and j, it represents the query time of the string, after compression. The answer of this query in Karp-Rabin was a fingerprint of substring $S(i, j)$. In Karp-Rabin representation $O(n)$ represents first. Space data structures and the answer from the data structure forms quires without decompressing any characters. The straight line program (SLP) gets $O(\log N)$ query time, then for linear SLPs get $O(\log\text{-}\log N)$ at query time. These results extend to solve the longest common extension problem in query time as $O(\log N \log l)$ and $O(\log l \log\text{-}\log l + \log\text{-}\log N)$ for SLPs and linear SLPs respectively. In this equation, "l" denotes the length of LCE [23]. Although it can solve this various limitation, it is still an open problem to determine if an $O(\log N)$ time solution using $O(n)$ space.

Mansouri *et al.* [24] focus on the model-based compression algorithm. The model-based algorithm is mainly applied for the compression of fingerprint images. The parallel lines with arbitrary widths, identical orientation, gray local values for background and similar gray level values are based on this model-based compression. This algorithm is referred to as parallel stocked multi-line (PSML). The algorithm is developed based on adaptive geometrical wallet which forms PSML for preserving fingerprint structure and minutiae in robustness. Over wavelet transform and JPEG 2000 in PSNR value with the visual quality of compressed images and its effect are in the automatic fingerprint identification system are some of the advantages of the proposed system, JPEG 2000 with extreme compression rates with uncompressed images are 267:1, the value is 49.41%, 6.22% respectively. For the coded images, an adaptive modulation can be used. And in AGW based transform, it divides the fingerprint image into patches and is used in the predefined dictionary. This algorithm is used for dividing images with image approximation algorithm. By using this algorithm, the structure of fingerprint images is preserved even in extreme compression ratio. And it gave the superior performance of the PSML algorithm over PSNR values and preservation of minutiae by AFIS for identification. Even though it possesses added complication and an unknown byte/pixel relationship, many drawbacks occur.

Shao *et al.* [25] proposed the sparse representation. The existing technique compress only still and color images, and PSNR also becomes an important limitation in the image compression, and it possesses higher complexities. To overcome this problem, a new compression method is used and known to be sparse representation. The algorithm is less serious than JPEG. One of the main algorithm used in compression is K-SVD. It occurs better than the compression results. But it has some of the difficulties, as developing the compressive algorithm for fingerprint images. During compression and decompression, the new sparse algorithm contains minutiae robustness for further development. But it also has some limitations. Such drawbacks are the quality of the compression images,and optimization *etc.*

Gottschlich *et al.* [26] introduced an extended quadratic differential (XQD) with orientation field (OF). The orientation field is used for the geometric representation. For the compression of the images, the OF compression is used for further compression process. It estimates orientation field and compression with automatically or semi-automatically, high fidelity and depending on high image quality. The existing method is (QD) quadratic differential which is used for the automatic orientation and compressing of the fingerprint images but it has low orientation and image quality. To overcome the above limitations, the extended quadratic differential (XQD) is introduced. The XQD has a lot of advantages as the model lies in the small number of parameters, each consists of obvious geometric meaning. After the compressing gets completed, the image possesses minimal runtime, minimal deviation from OF, file size increase of the stored XQD *etc.* Thus, the compression is a semi-automatic model with OF representation. The minutiae and huge image compression are still an open problem.

Anurakphanawan and Lamsrichan [27] focused on the different WSQ, CAWDR and JPEG 2000 for the evaluation of fingerprint image compression. Smart card, ID cards *etc.* are some of the existing technologies which are not reliable for secured electronic transactions. A Euclidean distance method is used to find matched fingerprint recognition between WSQ, JPEG 2000, CAWDR (context-based adaptive wavelet difference reduction). Anurakphanawan and Lamsrichan propose the subband-reduced CAWDR, which is used for comparative recognition performance to conventional CAWDR. The CAWDR and JPEG 2000 are not the same databases. Developing current image compression, recognition performance, complexity, and encoding algorithm are the challenges faced by this system.

3. PROPOSED FINGERPRINT IMAGE CODER

Fig. 1 shows the process flow of the proposed work. There are three phases of working principle carried out in the proposed scheme. The median filter is used to smoothen the image from any sensor or environment noise factors in the first pre-processing phase. The second phase is the ridge feature extraction. It selects the most specific features for fingerprint identification. The compression phase is the final phase, a POST coder is proposed to compress the image.

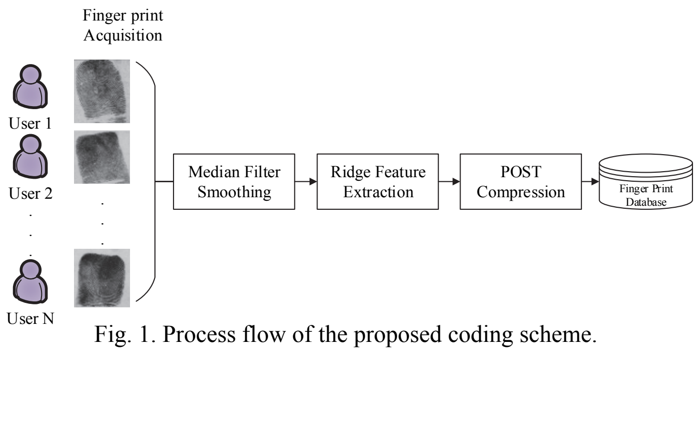


Fig. 1. Process flow of the proposed coding scheme.

3.1 Adjustment of Finger Print Image

The FVC2004 dataset is considered as the fingerprint database for the proposed framework. The fingerprint database $F(D)$ with input images can be represented as,

$$F = f_d,\ d = 1, 2, \ldots, n. \tag{1}$$

Where d is the image in the database from n number of images. Let us consider a user input fingerprint image taken from a biometric device. The edge details of the input image can be preserved by applying the median filter. The noise effect can be reduced by smoothing with the non-linear digital filtering to preserve the edge information of the fingerprint for AFIS system.

In pre-processing, the median filter is used to reduce the effect of noise by smoothing. It is a nonlinear digital filtering technique, which can preserve as many edges in the image as possible while removing noise. In the fingerprint identification system, the edge details are most important, so the median filter performs that action. The median filter works based on the fixed window size and the average median filter for $f_{3\times3}$ window can be represented as,

$$M(x,y) = \begin{cases} \text{medfilt2}(f_{3\times3}), & |\text{medfilt2}(f_{3\times3})| < \partial \times f(x,y) \\ f(x,y), & \text{otherwise} \end{cases}. \tag{2}$$

In the above equation, ∂ is a modifier that can be randomly chosen to be 0.3. The medfilt2 function performs median filtering of the image in two dimensions. Each output pixel contains the median value in a 3-by-3 neighborhood around the corresponding pixel in the input image.

3.2 Ridge-based Feature Extraction

After smoothing, the image is attained for segmentation because the details or objects from the fingerprint are only necessary for fingerprint identification. If we apply the feature extraction, the fingerprint structure can be easily identified by the probability map which is generated from the median filtered image M_d by applying feature extraction.

First of all the image is divided into local blocks of size $m*n$ and the ridge based features are extracted from the local blocks. In the fingerprint image, it may contain ridge like noisy patterns, so here, ridge feature extraction is used to extract the ridge properties of the image.

Average inter-ridge distance (AID): Gradient approach [28] is used to compute the ridge peaks from each block. The absolute difference between two successive peaks can be defined as

$$AID = \frac{\sum_{l=1}^{N} \beta_l}{N-1}. \tag{3}$$

The distance between two successive peak values is denoted by β_l and N denotes the number of peaks in the ridges.

The variance of peak ridge height (VPRH): It estimates the variance of the peak heights in the ridges. The ridge pressure of each local block can be expressed as RHV.

$$VPRH = \frac{\sum_{l=1}^{N} RH_l - RH_{mean}}{N-1} \tag{4}$$

Where RH_l is the ridge height of the lth ridge and RH_{mean} is the mean of peak ridge height across all the blocks.

Ridge frequency (RF): The Short Time Fourier Transform (STFT) [29] can be applied to the local block to extract the frequency of the ridges. A set of directional filters with varying frequencies are multiplied with the spectrum of frequency response for magnitude. The maximum frequency response obtained at the filter is taken as the ridge frequency.

$$RF = \arg\max_l \left(\sum_{p=1}^{M} \sum_{q=1}^{N} |F(p,q)| * D_r(p,q) \right) \tag{5}$$

Where, $D_r(p, q)$ are the values obtained from the rth directional filter and $F(p, q)$ is the output of the Fourier transform for each block.

Angular Bandwidth (AB): The AB feature extraction is similar to RF. The peak response is calculated after STFT is applied on each local block. AB is obtained from estimated local orientation and the bandwidth of directional filter that provides the peak response for each block.

3.3 Feature Selection

The above four ridge based features are combined finally to form a probability map. The proposed algorithm utilizes an aggregation of five features. However, not all of them are equally distinctive for finger print verification. Therefore, we need to perform feature selection to select highly discriminative features to provide improved (and meaningful) output. The effectiveness of the extracted features is evaluated individually. Choosing a subset of relevant features for better performing the task at hand is a challenging research problem. Let W be the weight vector calculating the relevance of each feature i. The standard probability map for the feature selection is given as follows:

$$P(x) = W_i - (X_i - H_i)^2 + (X_i - M_i)^2 \tag{6}$$

where X_i refers to the ith training feature instances, H_i is the "near-hit" instance of i denoting the nearest neighbor of X_i that belongs to the same class of X_i, while M_i is the "near-miss" instance denoting the nearest neighbor of X_i belonging to its opposite class. Here, the nearest neighbor is calculated using Euclidean distance measure. It can be understood that the relevance of the weight value reduces if the near-hit of a particular point is at farther distance compared to its near-miss neighbour.

A new probability image is constructed in order to use the probability map further. The probability map $P(x)$ is the final mapping probability of all the features. The final image after the feature extraction probability map is described as,

$$F' = (1 - \omega)P(x). \tag{7}$$

Where ω is a weight to control the contributions of the probability map $P(x)$ and the original intensity. The main aim of this paper is to reduce the bit rate for a high quality. The highly efficient features for the AFIS system are extracted. Before storing the image in the database, the compression scheme is carried out on the probability map because a lot of storage space is required for high-quality image. In order to reduce the size of the image size, a compression scheme called POST is described in detail in the below section.

Pattern Optimization from Subset Tree (POST) compression scheme

POST coding scheme is introduced in this paper with the objective to reduce the size of the fingerprint image before transmission and storing. The most significant results considered in each iteration of the POST are Relevant Pixel Index (RPI), Irrelevant Pixel Index (IPI) and Irrelevant Gang Index (IGI). The POST operation will be performed on each block but at a time a specific block will be selected for the operation. The most significant bits of the selected block can be represented as RPI, the insignificant pixels other than the significant pixels are referred to as IPI and the insignificant blocks other than the selected blocks can be represented as IGI. The pixel values below the threshold would be considered as irrelevant pixels and pixel value equal or greater than threshold would be considered as relevant pixels. Initially, set the RPI as a null set. Basically, the most significant bit (MSB) contains the relevant information and the least significant bit (LSB) contains few information. The size of the image can be reduced by removing some bits. The LSB subband coefficients are in the IPI and the IGI contain the descendant subsets of LSB subbands. The blocks can be selected as a tree based structure with its root and child nodes. The procedure for the POST compression scheme is described in the below steps.

Step 1: Initialization

Initially, divide the image into equal sized blocks of size $m \times n$. We consider two major factors to initialize the algorithms are magnitude θ and threshold λ. The maximum range of magnitude will decide the threshold for further operations.

$$\theta = \lfloor \log_2(\max\{F'(x, y)\}) \rfloor \tag{8}$$

Where θ decides the threshold λ. It can be determined by the maximum magnitude of all the coefficients in the image. The threshold from the magnitude θ can be represented as,

$$\lambda = 2^{\theta}. \tag{9}$$

By setting up the threshold, the image details can be preserved because the threshold operation is repeated until the scanning for every pixel up to the last block.

Step 2: Sorting

The final bit stream can be produced at the resultant of sorting operation. The relevant pixels are selected as 1 and the irrelevant pixels are selected as 0.

The sorting operation

$$H(x,y)=\begin{cases}1 & \text{if } f'(x)>\lambda \\ 0 & \text{if } f'(x)\leq\lambda\end{cases}. \tag{10}$$

The binary representation can be given for the output of IPI. The significant pixels representing 1 are placed on the RPI list and the remaining pixels remain in the IPI for the current block. The remaining blocks details are entered in the IGI.

Step 3: Refinement Process

The refinement process is applied for each entry in the RPI. The final output is considered as the θth MSB.

Step 4: Quantization process

This will continue until θ value reach 0. In this step, the θ value is decremented by 1 and repeat the steps 2, 3 and 4 until zero. The same process is repeated up to the final subset. The final matrix representation for the LSP subset is given as

$$H(x,y)=\begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1n} \\ h_{21} & h_{22} & \cdots & h_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ h_{n1} & h_{n2} & \cdots & h_{nn} \end{bmatrix}. \tag{11}$$

The final bit stream from the LSP subset after several iterations with their position is ready for transmission. At each iteration, we will have a stream of bits. For example, if you have 10 blocks, probably you may get 10 streams of bits. In this stream of bits, there is a possibility to occur similar patterns. The similar patterns are repeated several times. If we select an optimal pattern during transmission, surely the bit rate will get reduce.

Step 5: Bit Stream Pattern Optimization

Let us consider a stream of bit patterns. The bit stream pattern optimization has the major goal to select the size reduced pattern. In order to select the optimal pattern with reduced size, a most famous particle swarm optimization (PSO) is considered. This algorithm will work depending upon the principle of swarm behaviour or fish schooling.

The objective function of the PSO is stated as

$$f(x)=\min\{Q(R)\}. \tag{12}$$

Here, $Q(R)$ is the compression ratio for the attribute subset R. First of all, the PSO is initialized with a set of random patterns called particles and then searches for the optimal pattern with the objective of reduced bit size by updating several iterations. Then evaluate the fitness function for each set of patterns and that patterns are stored as pbest. Then another best value is evaluated from all the patterns is determined as the gbest. The fitness evaluation can be computed as

$$Q(R) = 1 - \frac{\eta}{\kappa}. \tag{13}$$

Here, η is the storage size needed to represent the original image. κ is the total storage size of all the arrays together that are needed to hold the compression information that would be needed to recover the image. After finding the best values, the particle swarm optimizer will update the particle velocity and particle position. The pattern velocity can be determined as

$$V'_{ij} = V_{ij} + \phi_1 * \text{rand}() * (pbest[] - present[]) + \phi_2 * \text{rand}() * (gbest[] - present[]). \tag{14}$$

Where, V_{ij} is the velocity of the pattern, ϕ_1 and ϕ_2 are learning factors, and () is a random number between (0, 1), present[] is the current pattern solution.

The pattern position can be updated as

$$present[] = present[] + V_{ij}. \tag{15}$$

After several sets of iterations, finally, generate a global best of patterns to achieve the minimum storage space. Then the final selected pattern and its position are transmitted and stored in the database. In the Decompression stage, the inverse operation is carried out to extract the original fingerprint image.

Algorithm 1: POST compression scheme

Input: Set of feature coefficients (F')
Output: optimized pattern with minimum size
Step 1: Initialization
Step 2: Sorting
Step 3: Refinement
Step 4: Quantization
PSO pattern optimization
Input: bit stream patterns
For each image stream of bits and its position
Initialize the set of patterns
For each bit stream patterns
Calculate fitness value
    If the fitness value is better than the best fitness value (pBest) in history
        Set current value as the new pBest
    End
End
Choose the bit stream pattern with the best fitness value of all the particles as the gBest
For each bit stream pattern
Calculate bit stream pattern velocity according to Eq. (13)
Update bit stream pattern position according to Eq. (14)
End
Repeat until minimum size.
End

4. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed system is evaluated in the MATLAB 2017 simulation software to evaluate the compression results. The FVC2004 dataset [30] is used for the evaluation of results on finger prints. The database detail is described in Table 1. The performance is evaluated in terms of PSNR (Peak Signal to Noise Ratio), EER (Equal Error Rate) and CR (Compression Ratio).

Table 1. FVC2004 dataset description.

Database	Sensor or scanners	Size	Resolution (dpi)
FVC2004 DB1	Synthetic Generator	288×384	~500
FVC2004 DB2	Thermal sweeping sensor	300×480	512
FVC2004 DB3	Optical sensor	328×364	500
FVC2004 DB4	Optical sensor	640×480	500

4.1 Evaluation Metrics

Normally, the performance of the compression scheme is evaluated in terms of visual appearance, compression ratio, and information loss. Generally, the visual appearance cannot be measured because it depends upon the observer. The information loss can be measured in terms of PSNR, EER, and bpp.

Compression Ratio: The compression ratio can be measured as

$$CR = \left(1 - \frac{Compressed\ Size}{Original\ Size}\right) \times 100. \tag{16}$$

Bit per pixel (bpp): The inversion of compression ratio is the bpp.

$$bpp = \frac{Total\ no.\ of\ bit\ stream\ after\ compression}{Total\ no.\ of\ bit\ stream\ of\ the\ original\ image} \tag{17}$$

Peak Signal to Noise Ratio (PSNR): The distortion in the compressed results can be measured using PSNR. If PSNR is high, the image quality is good.

$$PSNR = 10 \log_{10} \frac{255^2}{MSE}, \tag{18}$$

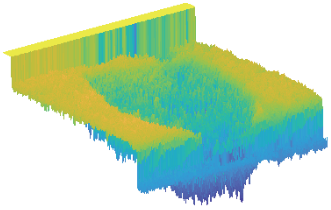
where $MSE = \frac{1}{N^2}\sum_{i,j}\left(F_{original}(i, j) - F_{compressed}(i, j)\right)^2$. The dimension of the image is represented as N, $F_{original}(i, j)$ is the original image and $F_{compressed}(i, j)$ is the compressed image.

4.2 Result Analysis

The performance of the compressed image with the original image can be represented with the 3D plot in the below Figs. 2-5.


(a) Original image.


(b) Compressed image.


(c) 3D plot for the original image.

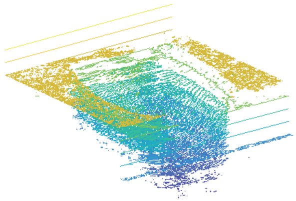
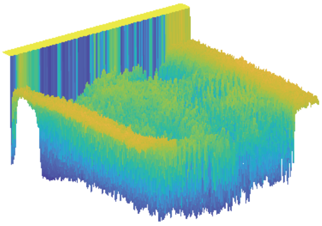

(d) 3D plot for the compressed image.

Fig. 2. 3D plot for the original image and the compressed image on DB1 from the FVC- 2004 dataset.


(a) Original image.


(b) Compressed image.


(c) 3D plot for the original image.

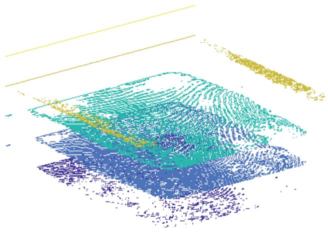
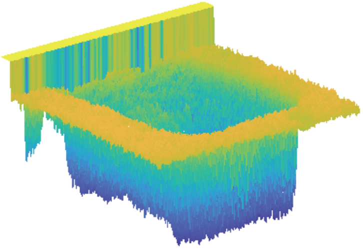

(d) 3D plot for the compressed image.

Fig. 3. 3D plot for the original image and the compressed image on DB2 from the FVC- 2004 dataset.


(a) Original image.


(b) Compressed image.


(c) 3D plot for the original image.

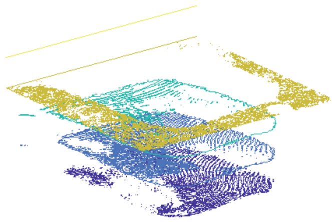
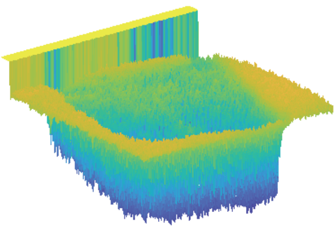

(d) 3D plot for the compressed image.

Fig. 4. 3D plot for the original image and the compressed image on DB3 from the FVC- 2004 dataset.


(a) Original image.


(b) Compressed image.


(c) 3D plot for the original image.

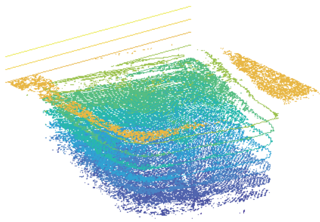

(d) 3D plot for the compressed image.

Fig. 5. 3D plot for the original image and the compressed image on DB4 from the FVC- 2004 dataset.

Fig. 2 represents the compressed results in the FVC2004 of size 288×384. Similarly, the compression results for the Figs. 3-5 can be represented with the image size 300×480, 328×364 and 640×480. The 3D plot represents the image size is reduced after the compression as compared with the original image. The POST compression scheme is performed on the each block of the image. So, the resultant compression scheme performs an improved results with low bit rate for high-quality images.

Fig. 6 shows the comparative chart between PSNR and compression ratio. In Fig. 6, the proposed scheme is compared with the PSML (Parallel Stroked Multi Line) scheme and wedgelets transform for FVC database. The PSML scheme works based on Adaptive Geometrical Wavelet based transform for encoding. It's a model based compression algorithm. It is specifically proposed to compress the fingerprint image data. Despite its efficient performance, this algorithm requires a large database for training, which must correspond to future acquired fingerprint images and produce a large dictionary that has to be present in both encoder and decoder sides. The wedgelet transform is based on exhaustive search which requires assessment of all wedgelet atoms and hence is prohibitively slow. The proposed POST algorithm has significant advantages over PSML and Wedgelets Transform in terms of PSNR value on Automatic Fingerprint Identification Systems (AFIS). It shows that the PSNR value of the proposed scheme is improved for the corresponding compression ratio. So, we can clearly say that the quality of the image after the compression can be improved for the proposed scheme as compared with the existing PSML and wedgelets transform approaches.

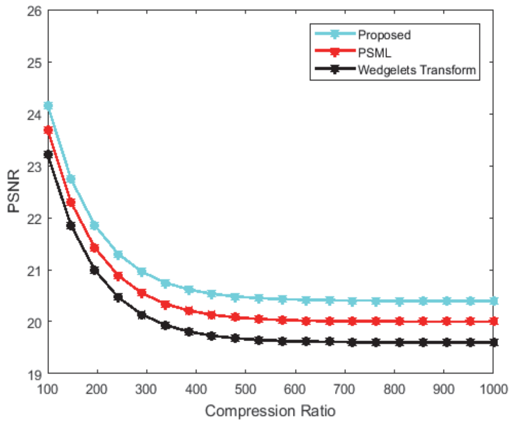


Fig. 6. PSNR vs compression ratio for FVC database.

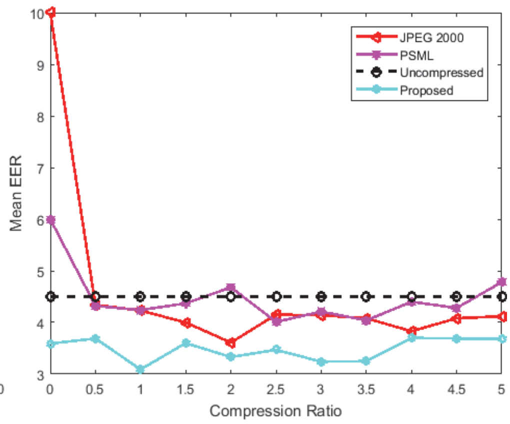


Fig. 7. Mean EER vs Compression Ratio for FVC database.

The error rate is minimized for the proposed scheme. The system performance is measured using the EER and the measure clearly show that our proposed scheme performs better compression as compared with the existing JPEG 2000, PSML, and uncompressed schemes. In Fig. 7, mean EER value is achieved for each compression ratio and compression algorithm. The mean EER value of JPEG2000 and PSML increases up to 50% and 20%, which means the identification algorithm works like a random algorithm and the compressed images cannot be distinguished. However, the mean EER value of proposed POST algorithm remains in the acceptable range and the compressed images can be distinguished from each other.

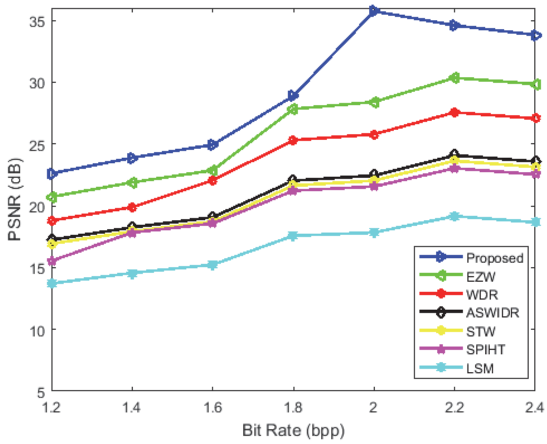


Fig. 8. Compression result at 0.15 bpp.

The compression scheme can be compared with the existing algorithm such as Embedded Zerotree Wavelet (EZW) [31], spatial orientation Tree Wavelet (STW) [32], Set Partitioning in Hierarchical Trees (SPIHT) [33], Wavelet Difference Reduction (WDR) [34], and Adaptively Scanned Wavelet Difference Reduction (ASWDR) [35, 36]. The above Fig. 8 shows that the compression result between PSNR and bpp performs better results as compared with the existing approaches. In Fig. 8, the proposed image compression scheme is compared with the standard image compression scheme in terms of PSNR. The PSNR results for the existing algorithms is not specifically evaluated for the fingerprint images. It's a common compression scheme for lossy and lossless compression. The PSNR value for the existing schemes are compared in terms of bpp. Although, the existing works in Fig. 8 are wavelet based entropy-coded scheme but a large bit budget spent on encoding. The number of bits required to store the pixel of the image is high. The proposed scheme overcomes the drawback with an optimization scheme and achieves better PSNR.

Table 2. Comparative results for compression evaluation metrics.

Method	PSNR	CR
Ben and Jemai [37]	40.0	70.1
Huifang and Mo [38]	45.1	87.5
Savant and Admuthe [39]	23.3	87.5
Dutta *et al.* [40]	28.3	86.72
Karthikeyan and Sreekumar [41]	22.4	–
Saleh [42]	27.3	71.9
Proposed	32.2	92.5

Table 2 shows the performance evaluation of the compression scheme in terms of neural network for training with the proposed method. As compared with the techniques proposed by various authors from reference [37-42], the PSNR value for the proposed scheme will be in the normal range. Here, we are using the lossy compression scheme but the range of PSNR will be at a nominal range. It shows that the proposed compression scheme reduces the loss of information.

5. CONCLUSION

Thus, the paper concludes that the proposed image coding scheme called POST performs better compression ratio and the size of the image is significantly reduced for high-quality images. This paper mainly focuses the bit rate reduction while storing the fingerprint image in the AFIS system. There is no need to store the entire information because AFIS system verifies the finger print details of the user. In order to verify the fingerprint details, the ridge feature is necessary, so the ridge features are extracted from the image before compression. After extracting the features, an image coder called POST is proposed to compress the image before storing. The proposed algorithm performs sorting, refinement, quantization and finally, PSO based pattern optimization for the reduction of image size. The proposed scheme provides better coding efficiency as compared with the other color coding standard schemes. It is robust over noise and attains an efficient convergence time during compression.

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V. Rekha received her B.Sc, M.C.A. and M.Phil degrees in Computer Science, Computer Applications and Computer Science from Manonmaniam Sundaranar University, Tirunelveli, Anna University, Chennai and Manonmaniam Sundaranar University, Tirunelveli in 2003, 2006 and 2007 respectively. She joined Ponjesly College of Engineering as a Lecturer in 2006 and then became an Assistant Professor in 2007. She is currently working toward Ph.D. degree in Computer Science at Ponjesly College of Engineering. Her research work includes biometrics, image compression, cryptography.

V. Kavitha obtained her B.E. degree in Computer Science and Engineering in 1996 from the Noorul Islam College of Engineering and M.E. degree in Computer Science and Engineering in 2000 from Mepco Schlenk Engineering College. She received Ph.D. degree in Computer Science and Engineering from Anna University, Chennai in the year 2009. Right from 1996, she is in the Department of Computer Science and Engineering under various designations. Presently she is working as an Associate Professor and Head in the Department of Computer Science and Engineering at University College of Engineering, Kancheepuram, Tamil Nadu, India. Her research interests are network security and cloud computing.