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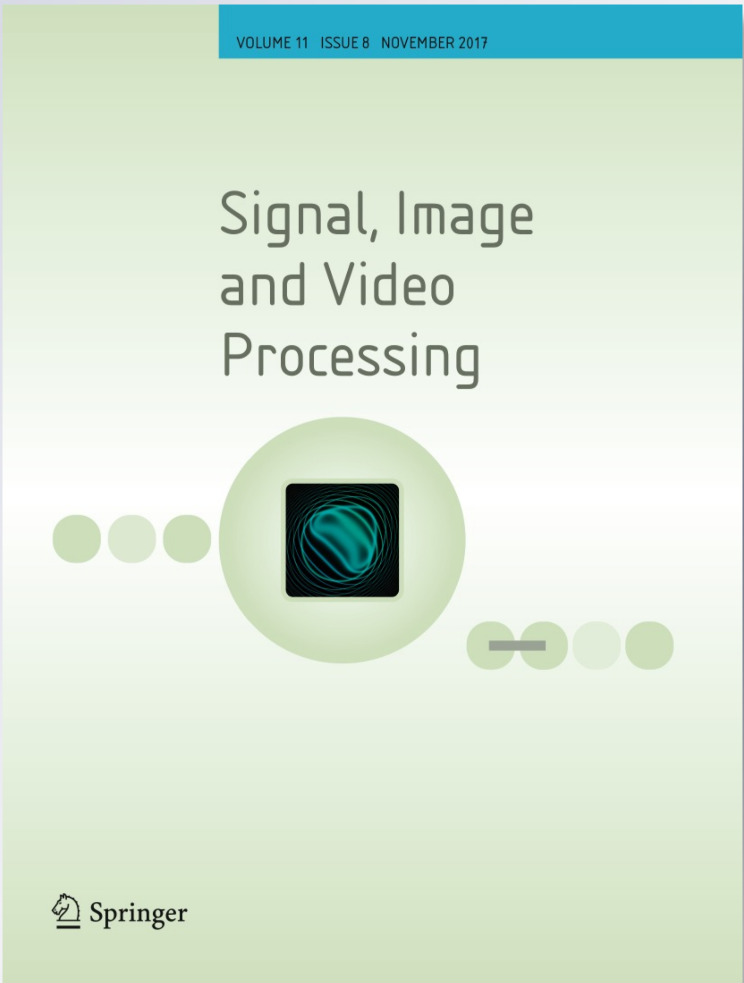

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ORIGINAL PAPER

Extreme compression of fingerprint image databases using the model-based transform

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Abstract In this paper, a model-based compression algorithm is proposed to compress the fingerprint image data. The proposed model is based on parallel lines with identical orientations, arbitrary widths, and similar gray-level values positioned on a rectangle with a constant gray-level value as the background. This algorithm is referred to as Parallel Stroked Multi Line (PSML). A compression algorithm is developed based on Adaptive Geometrical Wavelet which employs PSML to preserve the fingerprint structure and minutiae. The proposed PSML algorithm has significant advantages over Wedgelets Transform and JPEG2000 in terms of PSNR value, visual quality of the compressed images, and compression effect on Automatic Fingerprint Identification Systems (AFIS). On the *U.are.U 400* database, the mean EER rate for uncompressed images is 4.54%, whereas at extreme compression rates, like 267:1, this value is 49.41% and 6.22% for JPEG2000 and PSML, respectively. The results show a significant improvement compared to the standard JPEG2000 algorithm.

Keywords Parallel Stroked Multi Line · Adaptive Geometrical Wavelet · Model-based compression · Fingerprint image compression · Large fingerprint database

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1 Introduction

Biometric-based human identification and authentication systems rely on several biometric modalities including fingerprint [11], palm, face [8], iris, gait [21], human activity and heart sound [1]. Among these, the fingerprint is the most widely used modality. In Automated Fingerprint Identification Systems (AFIS), the digitized form of fingerprint data is used to perform matching and verification. With growing application of fingerprint-based systems, the size of fingerprint enrollment databases has increased significantly. Therefore, an efficient storage mechanism is required to handle this massive bank of data.

Figure 1 illustrates the mechanism of general AFIS. After acquiring the fingerprints by the biometric device, they are transmitted to enrollment server to extract minutiae information. Afterward, the minutiae information is stored in the database. When a new fingerprint image is enrolled, to identify the fingerprint which matches this image, an algorithm is employed to find matching between the extracted information from the new fingerprint and the minutiae stored in the database [15]. Typically, the fingerprint images are also stored in the database for further applications such as new enrollment algorithms.

There has been a host of studies on each part of AFIS. In Fig. 1, these parts are indicated by numbers 1–4. This paper focuses on the compression algorithm (part 2) which should generate compressed image with high compression rate (first condition), while maintaining the discriminative information required for the next step (second condition). For assessing the compression quality, the most popular metric in the field is peak signal-to-noise ratio (PSNR), but this measure can only fulfill the first condition. To meet the second condition, other metrics such as Spectral Image Validation and Verification (SIVV) are used. However, the best metrics that can evaluate

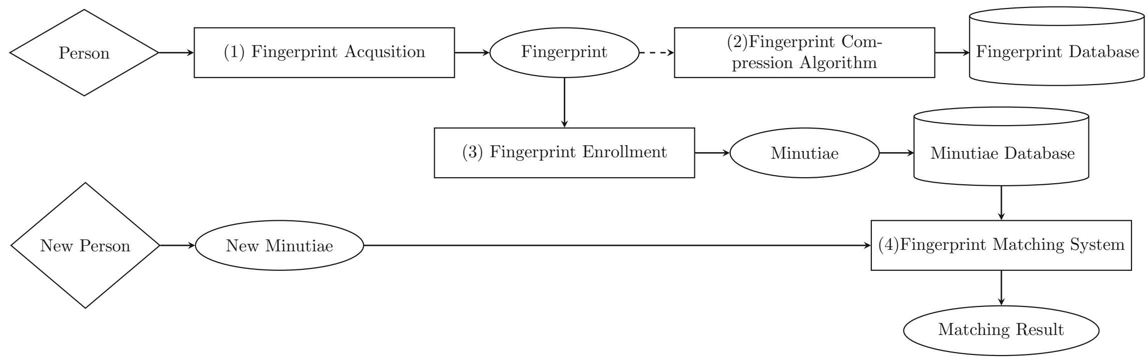


Fig. 1 General AFIS system

the compression quality in AFIS systems are false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER) [20].

The ISO/IEC 19794-4 standard allows fingerprint image data to be stored in a lossy manner in Joint Photographic Experts Group (JPEG), wavelet transform/scalar quantization (WSQ), and JPEG2000 formats. Nonetheless, given the deficiencies of ISO/IEC 19794-4 standard, researchers seek to develop new methods for the compression of fingerprint image data. These researches are usually dedicated to four categories.

The first category includes researches that review, compare, and analyze existing methods proposed for compressing fingerprint images, any type of images, or data. They strive to identify the best solution for the compression of fingerprint images. In the previous studies such as [2,3,14,16], most formats like JPEG, WSQ, JPEG2000, wavelet, fractal coding, EZW, Context-based Adaptive Wavelet Difference Reduction (CAWDR), Set Partitioning in Hierarchical Trees (SPIHT), and Predictive Residual Vector Quantization (PRVQ) have been compared. The second category includes researches that focus on energy and coefficient distribution on discrete cosine transform (DCT) [27,28] and wavelet transform [10] using optimization methods such as genetic algorithm [22,23] and simulated annealing [25]. The third category includes researches which focus on structures found in fingerprint images such as *ridge* [19] and *valley* [7] and use them for compression. These strong structures have led researchers to use Self-Organizing Map (SOM) [17], k-SVD [24], and Recursive Least Squares Dictionary Learning Algorithm (RLS-DLA) [6] for Sparse Representation (SR) of image patches. The last category includes researches (such as [26,31]) cannot be regarded as individual categories because they reflect enormous heterogeneity.

To the best of our knowledge, the best algorithm introduced for compressing fingerprint images is K-SVD-SR [24], which is based on compress sensing (CS). 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. In this paper, a model-based transform without pre-trained dictionary is proposed. The proposed algorithm has a significant performance in extreme compression ratio that allows compressing fingerprint images at compression ratio such as 250:1, with negligible variation in the identification rate of AFIS.

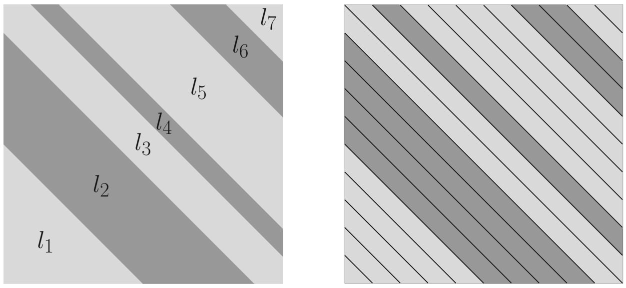
2 Proposed method

In this section, a new transform based on Adaptive Geometrical Wavelet (AGW) is proposed to encode images. All AGW-based transforms divide the image into patches and then use a predefined dictionary to approximate them. In the rest of this section, the dictionary structure, the algorithm used for dividing images, and the image approximation algorithm are described in brief.

2.1 Dictionary structure

AGW uses the geometry of structures in image domain to define a model. By fitting specific parameters, this model must approximate any random patch of image domain, with minimal distortion. The proposed model is defined by a rectangle which is filled by some non-overlapping lines with arbitrary width and fixed orientation. Each line belongs to either the foreground or background, so the rectangle is filled by two gray-level values. Figure 2a shows the defined model. For the sake of simplicity, each line with the width w is considered as w lines with a unit width (see Fig. 2b). This model, called *Parallel Stroked Multi Line* (PSML), is defined as follows.

Definition 1 Assume a rectangle S with the arbitrary size $m \times n$ and parameters θ, p, c_1, and c_2. Suppose S is filled by p non-overlapping lines with a unit width and slope θ. Let denote c_1 and c_2 as gray-level values of the foreground and background, respectively. Given that each line belongs to either the foreground or background, the rectangle S defines



(a) **(b)**

Fig. 2 **a** PSML model and **b** equivalent simple model

a gray-level image. This image forms the Parallel Stroked Multi Line model.

To determine the parameters required to represent the model, the gray level of each line can be represented by just one bit of memory (zero means c_1 and one means c_2). Thus, the gray-level value of all lines in S can be represented by a binary stream $G = g_1 g_2 \cdots g_p$. Therefore, PSML can be represented just with parameters θ, c_1, c_2, and G.

In particular, when all lines of the gray-level value belong to the foreground or background, a simple version of PSML called *constant model* should be used. The constant model is a rectangle with constant gray-level value that requires only the parameter c for representation.

2.2 Transform analysis of image

To approximate an image, a quadtree structure is used to divide the image into patches hierarchically. There are two cases for each node of the quadtree: (1) dividing into four children and (2) approximating with a constant model or PSML. Eventually, an image is approximated with an equivalent quadtree encoded for saving/restoring or transmission action. To encode the quadtree in a simple way, one bit is considered for each node indicating whether the node is divided or approximated. In the second case, one more bit is required to determine whether this node is approximated by a constant or by a PSML model. For each model, a few more bits are required to store the model. It will be discussed in the next section.

A basic algorithm which is used to obtain the best approximation of the image consists of two steps. In the first step, the image is fully decomposed by quadtree. Then, for each node, the proposed models are used to obtain the best approximation of current rectangle with the minimum square error. In the second step, a bottom-up optimization pruning algorithm is applied to the decomposition tree to obtain the best quality approximation image with the minimum number of model instances. In fact, the following weighted cost function is minimized:

$$R_\lambda = \min_P \left\{ \| F - F_T \|_2^2 + \lambda^2 K \right\},$$

where P is the homogeneous partition of an image, F denotes the original image, F_T is the image approximated by the proposed model, K is the number of bits required to encode the approximated image, and λ is the rate–distortion parameter.

3 Transform computation

In this section, to compute the transform, the parameter quantization of the model is described. Afterward, the time complexity of computation is analyzed. Then, to accelerate the proposed algorithm, an approximation method is introduced. Finally, a simple compression algorithm is utilized to compress the coefficients attained by the PSML algorithm.

3.1 Model parameters quantization

In the following, the parameter quantization is separately described. Parameter θ is in the range $[0, \pi)$ to cover all directions. For this purpose, two points C and O are used to represent orientations. Here, θ is the angle between the vertical axis of coordinate system and the line passing through two points C and O. Suppose that in rectangle S with $m \times n$ pixels, point C be fixed and located at pixel $C = (\lfloor \frac{m}{2} \rfloor, \lceil \frac{n}{2} \rceil)$. The location of point O varies and can be any pixel in the set $D_O = \{(0, y) | y = 0, \ldots, n-1\} \cup \{(x, n-1) | x = 0, \ldots, m-1\}$. Thus, the number of different values which can be assigned to parameter θ is equal to $m + n - 1$.

The value of gray-level parameters c_1 and c_2 is usually represented by 8 bits. However, the number of bits can be reduced to improve the compression ratio. Finally, the binary stream G is coded up to $\sqrt{m^2 + n^2}$ bits.

3.2 Fast patch approximation algorithm

Theorem 1 *The time complexity of PSML to approximate $n \times n$ patch using MSE metric is $O(n^3 2^n)$.*

Since approximation of each patch has an exponential time complexity, an approximation method is proposed to accelerate the computation. The proposed method is based on *hill-climbing* algorithm and can find the local maximum solution. In this method, the value of parameter θ is known and attempts are made to find parameter G. Using the value of this parameter, parameters c_1 and c_2 could be easily computed.

Algorithm 1 (Fast approximation)

Definition Let $G = g_1 g_2 \cdots g_p$ be a binary stream. Then, *neighbors of binary stream G* are denoted by binary stream G_k $(k = 1, \cdots, p)$ and defined as,

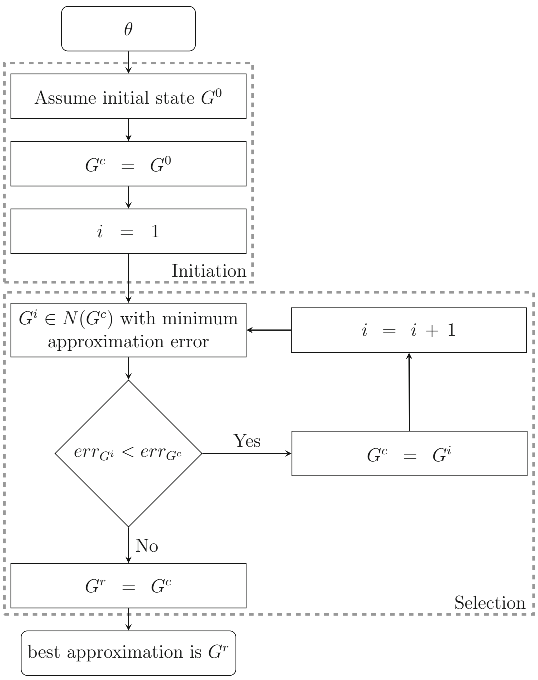


Fig. 3 The flowchart of Algorithm 1 (fast approximation) that compute patch parameters with fast approximation algorithm

$$G_k = g'_1 g'_2 \cdots g'_p \quad \begin{cases} g'_j = g_j & j \neq k \\ g'_j = \text{not}(g_j) & j = k \end{cases}$$

Moreover, denote all neighbors of state G with $N(G)$.

Initiation Assume the initial state be G^0 and the current state be G^c. To initialize the algorithm, set G^c=G^0 and $i = 1$.

Selection In each step i of the algorithm, let G^i denote a neighbor with the minimum approximation error in $N(G^c)$. If $\text{err}_{G^i} < \text{err}_{G^c}$, set $G^c = G^i$ and repeat the selection step again with $i = i + 1$. If $\text{err}_{G^i} \geq \text{err}_{G^c}$, set $G^r = G^i$ and proceed to the next step.

Output Given the value of parameter θ, the best approximation of the patch which yields the lowest error is G^r.

The flowchart of this algorithm is depicted in Fig. 3.

Here, the best initial state that is able to produce relatively optimal results is obtained empirically by the following algorithm.

Algorithm 2 (Initial state) Denote the mean of all gray-level values of the image pixels as c_m. For each line $l_i (i = 1, \ldots, p)$, if the mean gray-level value of all pixels in l_i is lower than c_m, then $g_i = 1$, else $g_i = 0$. The resulted binary stream forms the *initial state*.

Corollary 1 *According to the experimental results, the selection step of Algorithm 1 is repeated in order of $O(n)$.*

Lemma 1 *The best approximation of each $n \times n$ patch with fast approximation algorithm of PSML is computed in $O(n^5)$.*

Let us denote each line with the unit width in rectangle S by l_i $(i = 1, \ldots, p)$. Moreover, denote the sum of pixel gray-level values and the number of pixels belong to each line by N_i and S_i, respectively. Then, the c_1 and c_2 parameters are calculated as

$$c_1 = \frac{\sum_{\substack{i=1,\ldots,p \\ g_i=0}} S_i}{\sum_{\substack{i=1,\ldots,p \\ g_i=0}} N_i}\ ,\ c_2 = \frac{\sum_{\substack{i=1,\ldots,p \\ g_i=1}} S_i}{\sum_{\substack{i=1,\ldots,p \\ g_i=1}} N_i}.$$

This type of computation reduces the time complexity of calculating c_1 and c_2 parameters to $O(n)$. Surprisingly, this time complexity can be further reduced in accordance with the following lemma.

Lemma 2 *The time complexity of calculating c_1 and c_2 parameters for $G_k \in N(G)$ is $O(1)$.*

Proof Let us define $SC_{c,G}$ and $NC_{c,G}$ as

$$SC_{c,G} = \sum_{\substack{i=1,\ldots,p \\ g_i=c}} S_i\ ,\ NC_{c,G} = \sum_{\substack{i=1,\ldots,p \\ g_i=c}} N_i.$$

The parameters c_1^k and c_2^k of G_k can be computed as

$$\begin{cases} \text{if } g_i = 0 & c_1^k = \frac{SC_{0,G} - S_k}{NC_{0,G} - N_k},\ c_2^k = \frac{SC_{1,G} + S_k}{NC_{1,G} + N_k} \\ \text{if } g_i = 1 & c_1^k = \frac{SC_{0,G} + S_k}{NC_{0,G} + N_k},\ c_2^k = \frac{SC_{1,G} - S_k}{NC_{1,G} - N_k} \end{cases},$$

that takes $O(1)$ time complexity. Also, the parameters SC_{c,G^k} and NC_{c,G^k} can be computed in $O(1)$. □

By using Lemma 2, the approximation algorithm for each $n \times n$ patch is computed with following algorithm:

1 Do for each orientation θ	$O(n)$
2 Compute initial state $(S_i, N_i, SC_{c,G^0}, NC_{c,G^0})$	$O(n^2)$
3 Repeat the selection phase (Corollary 1)	$O(n)$
4 Do for each neighbor in $N(G^i)$	$O(n)$
5 Calculate c_1 and c_2 parameters for G_k (By Lemma 2)	$O(1)$

Theorem 2 *Time complexity of the fast approximation algorithm used to obtain the best approximation for the whole $n \times n$ image with Parallel Stroked Multi Line is $O(n^3)$.*

Proof Based on Lemma 2, the best approximation of each $m \times m$ patch is computed in $O(m^3)$. Without loss of generality, we assume that n is dyadic ($n = 2^J$). The proposed method is based on the Adaptive Geometrical Wavelet. Therefore, according to [5], when using quadtree for partitioning image, time complexity for the whole image, $\Psi(n)$, is computed as follows:

$$\begin{aligned} \Psi(n) &= \textstyle\sum_{j=0}^{J} 2^{2j} \times a \times (2^{J-j})^3 \\ &= a \textstyle\sum_{j=0}^{J} 2^{2J} 2^{(J-j)} = a 2^{2J} \textstyle\sum_{j=0}^{J} 2^j \\ &= a n^2 (2^{J+1} - 1) = a(2n^3 - n^2) \\ &= O(n^3), \end{aligned}$$

where a is a constant. □

3.3 Parameters compression

After approximating an image with quadtree structure and determining the parameters of atoms, they can be further compressed to improve the compression ratio. In this paper, LOCO-I prediction algorithm is used to predict gray-level parameters of each node in quadtree using the gray-level parameters of relative nodes in the quadtree structure. Also, to encode the predicted values and incorporate them into the binary file, Golomb–Rice coding is used.

4 Experimental results

To evaluate the proposed method, FVC databases and *U.are.U 400* database are used. The FVC databases are from *Fingerprint Verification Competition*. Each of these databases contains 10 fingers and 8 impressions per finger (80 fingerprints in total). The *U.are.U 400* database is published by *NeuroTechnology* that contains 65 fingers and 8 impressions per finger (520 fingerprints in total). In our experiments, we used Wedgelets Transform based on [5], JPEG2000 implementation provided by *Kakadu Software* and Verifinger SDK 7.1 presented by NeuroTechnology.

The first experiment involves a comparison between Wedgelets Transform [5] and PSML to illustrate the benefits of the model. The setting used for both algorithms includes 8 bits for gray-level value and is capable of building quadtree up to 8 levels without using the compression discussed in Sect. 3.3. Figure 4 shows the mean values of PSNR for all images in FVC2000 DB1_B and FVC2000 DB3_B databases for different values of bit per pixel (bpp). According to the results, with an increase in the compression ratio, the percentage of nodes in the quadtree, which is decorated by the model, is increased and these nodes grow in size. Since the PSML model is more compatible with the fingerprint structure than the Wedgelet model, the rate–distortion ratio of this model will have higher values.

The second experiment draws a comparison between coding algorithm recommended for fingerprint images [30]—JPEG2000 [4]—and PSML to illustrate the efficiency of rate–distortion, especially at higher compression ratios. The setting of the PSML transform uses arbitrary bits from 3 to 8 bits for gray-level value (i.e., the same bit rate for whole image), builds quadtree up to 8 levels, and uses compression method discussed at Sect. 3.3. Figure 5 shows the mean values of PSNR in all images in FVC2000 DB1_B and FVC2000 DB3_B databases for different values of bpp. According to the results, in overall, PSML significantly increases the compression ratio of the fingerprint images while maintaining

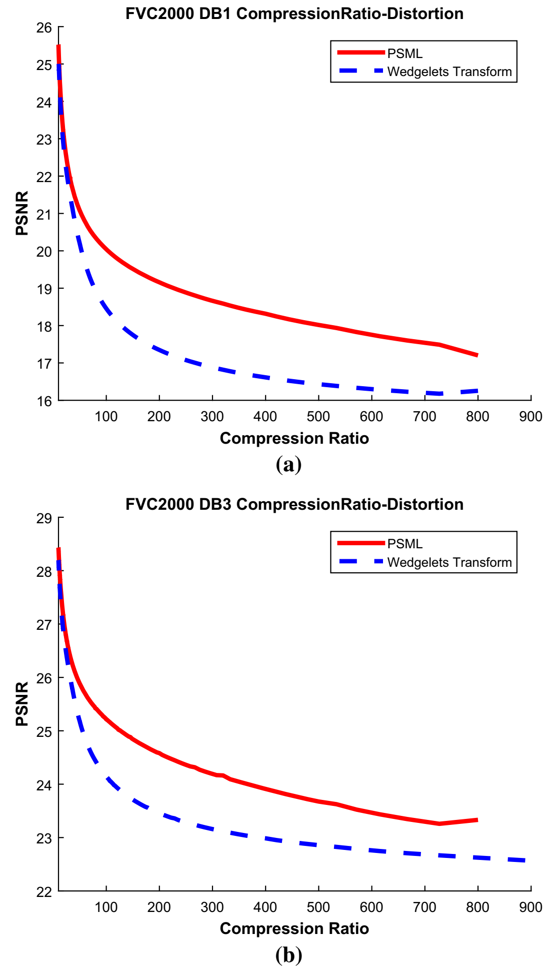


Fig. 4 Comparison between Wedgelets Transform and PSML Transform. PSNR mean value of all images in **a** FVC2000 DB1_B and **b** FVC2000 DB3_B

the quality. Figure 6 shows the fingerprint images encoded with both JPEG2000 and PSML algorithms. As seen, the discriminative information in images encoded by JPEG2000 cannot be identified, while the images encoded by PSML are of high quality that allow extracting minutiae information.

The third experiment involves discovering the influence of fingerprint compression on AFIS performance. This test was applied to *U.are.U 400* database and repeated for different compression ratios. At each compression ratio, all images are encoded with JPEG-2000 and the PSML algorithms at a specified ratio. Then, the VeriFinger tool is applied to all compressed images to obtain matching value of each pair of images. Finally, the mean EER value is achieved for each compression ratio and compression algorithm. As shown in Fig. 7, at compression ratio below 40:1, the EER value of both algorithm is similar, corresponding to the uncompressed images. At compression ratio above 40:1, the mean EER value of JPEG2000 increases up to 50%, which means

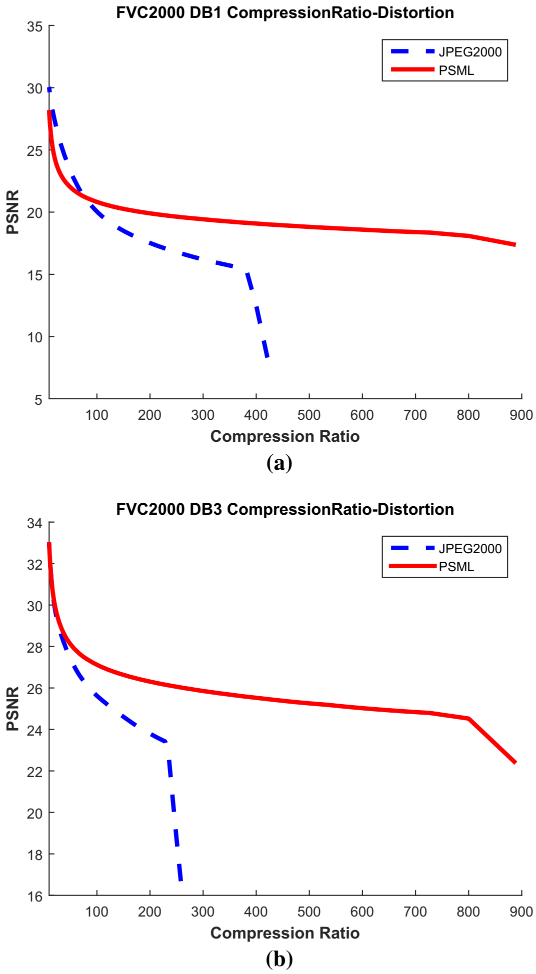


Fig. 5 Comparison between JPEG2000 and PSML Transform. PSNR mean value of all images in **a** FVC2000 DB1_B and **b** FVC2000 DB3_B

Fig. 6 Samples of compressed fingerprint images at high compression rates. '101_1.tif' from FVC2000 DB1_B **a** original image, **b**, **d** encoded with JPEG2000, **c**, **e** encoded with PSML. Compression ratio is **b**, **c** 178:1, **d**, **e** 320:1

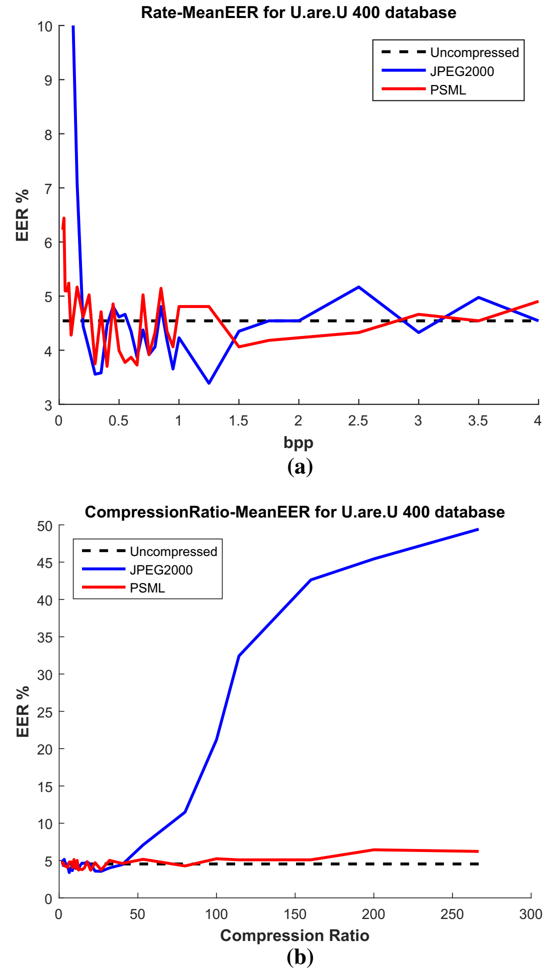


Fig. 7 The mean EER values obtained in experiment 3

the identification algorithm works like a random algorithm and the compressed images cannot be distinguished. However, the mean EER value of PSML algorithm remains in the acceptable range and the compressed images can be distinguished from each other.

The fourth experiment involves a comparison of different compression algorithms with respect to AFIS. According to the available information about comparison of these compression algorithms, we partitioned the fourth experiment in three parts. The first part includes comparison of PSML, WSQ, JPEG2000, and CAWDR [13] algorithms with respect to AFIS presented in [12] on FVC2002 DB3_B, and FVC2004 DB2_B databases (see Table 1). The results of WSQ, JPEG2000, and CAWDR are taken from [2]. The second part includes comparison of PSML, Wave Atom Decomposition (WA) [10], WSQ, SPIHT, and JPEG2000 algorithms with respect to an AFIS named Adjacent Orientation Vector [18] on FVC2004 DB1_B database (see Fig. 8). The results of WA, WSQ, SPIHT, and JPEG2000 are taken from [10]. The third part includes comparison of PSML and improved methods presented on [9] which are SPIHT+LSM and ASWDR+LSM, with respect to NIST AFIS (BOZORTH3 [29]) on FVC2004 DB3_B database. All the Table 1, Figs. 8, and 9 demonstrate that PSML algorithm has significant advantage over other algorithms, which confirms the results of the third experiment.

Table 1 Recognition accuracy of FVC2002 DB3_B and FVC2004 DB2_B (the results are taken from [2])

Compression Ratio		FVC2002 DB3_B 40	80	120	160	FVC2004 DB2_B 40	80	120	160
CAWDR	Correct	73	66	55	46	69	63	53	38
	Incorrect	7	14	25	34	11	17	27	42
	% Accuracy	91.25	82.50	68.75	57.50	86.25	78.75	66.25	47.50
	Avg. PSNR	28.24	26.70	25.90	25.49	27.94	25.29	24.00	23.13
JPEG2000	Correct	72	61	48	43	72	62	41	22
	Incorrect	8	19	32	37	8	18	39	58
	% Accuracy	90.00	76.25	60.00	53.16	90.00	77.50	51.25	27.50
	Avg. PSNR	28.03	26.18	25.24	24.93	27.66	24.70	23.06	22.04
WSQ	Correct	75	60	57	52	70	62	59	50
	Incorrect	5	20	23	28	10	18	21	30
	% Accuracy	93.75	75.00	71.25	65.00	87.50	77.50	73.75	62.50
	Avg. PSNR	26.90	25.75	25.23	24.94	26.69	24.38	23.29	22.60
PSML	Correct	77	77	76	77	75	74	70	75
	Incorrect	3	3	4	3	5	6	10	5
	% Accuracy	96.25	96.25	95.00	96.25	93.75	92.50	87.50	93.75
	Avg. PSNR	28.51	27.41	26.89	26.56	26.65	25.29	24.63	24.20

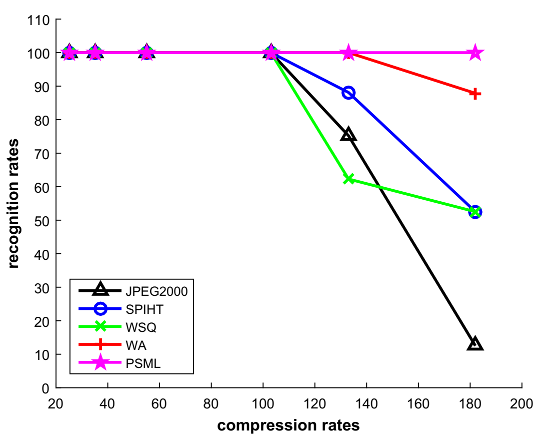


Fig. 8 Recognition rates as a function of compression rates for FVC2004 DB1_B database

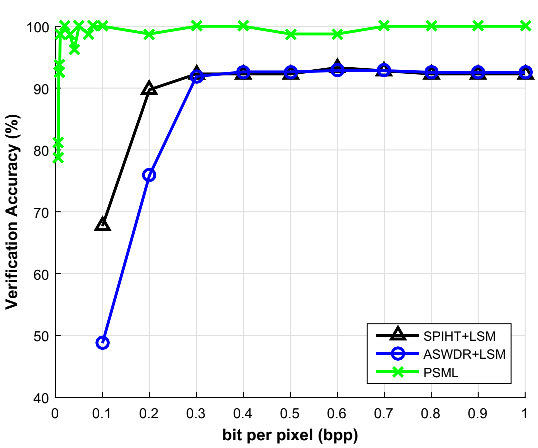


Fig. 9 Verification accuracy in different bit per pixel (bpp) for FVC2004 DB3_B database

5 Conclusion

In this paper, a simple structure called PSML model is proposed. Using this model in the compression algorithm, the structure of fingerprint images is preserved even at extreme compression ratios. In comparison with Wedgelets Transform and JPEG2000, the experiments show the superior performance of the PSML algorithm in term of PSNR values and preservation of minutiae information, which can be used by AFIS for identification.

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