A NEW METHOD OF FINGERPRINT AUTHENTICATION USING 2D WAVELETS

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ABSTRACT

A new approach for fingerprint verification, based on wavelets and pseudo Zernike moments (PZMs), is discussed. PZMs are robust to noisy images, invariant to rotation and have a good image reconstruction capability [4]. PZMs have been used for global analysis and so they are used to extract global features (the shape of the fingerprint image). Wavelets are good at local analysis and so they help to extract local features (minutiae) from a fingerprint. Therefore, this hybrid approach extracts most significant features from the fingerprint images and achieve better verification rate. Different types of wavelets are used for the study but the result shows that Symmlet orthonormal wavelet of order 8 gives best verification rate.

Keywords: *Fingerprint Verification; Minutiae; Global Features; Local Features; Features Extraction; Wavelets Pseudo Zernike Moments.*

1. INTRODUCTION

A fingerprint image is a pattern of ridges and valleys, with ridges as dark lines while valleys as light areas between the ridges. Ridges and valleys generally run parallel to each other, and their patterns can be analyzed on a global and local level. Global analysis of the fingerprint image is done to extract singular regions like loop, delta, and whorl (figure 1.1). Many matching algorithms use the center of the highest loop type singularity, known as the core, to pre-align fingerprint images for better results. These singularities help form the 5 major classes [1] of fingerprints (figure 1.2).

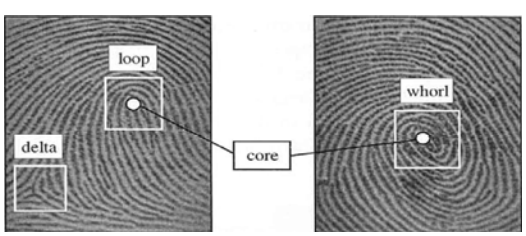

Fig 1.1 **Singular regions and core points**

While the global level analysis allows for a general classification of fingerprints, analyzing the image at the local level provides a significant amount of detail. These details are obtained by observing the locations of ridge-discontinuities, known as minutiae points. The most common out of different types of minutia (fig 1.3) are terminations (a ridge ending abruptly) and bifurcations (a ridge forks). The other types of minutiae are somehow or other combinations of terminations and bifurcations. For example, a lake is simply a sequence of two bifurcations in opposing directions, while an independent ridge is formed by two separate terminations within a close distance. Analyzing a fingerprint on the local level provides the necessary information to accurately distinguish one fingerprint from another.

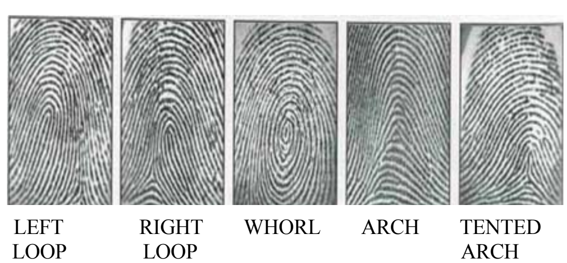

Fig 1.2 **Fingerprint classes**

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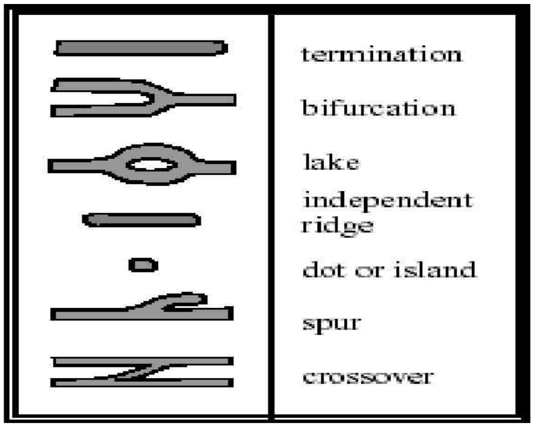

Fig 1.3 **Minutiae Types**

Wavelets are flexible-window Fourier-transform and they are used to decompose the image into different levels of resolution to ease information interpretation. Wavelets offer high temporal localization for high frequencies while offering good frequency resolution for low frequencies. Therefore, wavelet analysis can be utilized to extract local features from images [3]. In wavelet analysis, there is a mother wavelet and then there are wavelet coefficients derived from this mother wavelet. These coefficients are independent and they create a set of features of the actual fingerprint image at different resolutions.

PZMs are used to extract global features of the fingerprint image. Being orthogonal in nature, they extract image features independently with less information redundancy in a moment set. PZMs are also robust to noise and they extract a good amount of global image features. Therefore, this hybrid approach is able to take the best of both the worlds.

The proposed fingerprint verification system works in three stages. Firstly, the image is decomposed into different wavelet coefficients by applying wavelet transform. These wavelet coefficients can be adjusted to enhance and denoise the image. Wavelet decomposition results in reduced-resolution subband images, and so computational complexity is also reduced. Secondly, a lower-resolution fingerprint image is taken and PZMs are applied on it for feature extraction. Thirdly, a simple Euclidean distance metric is used for the dissimilarity matching.

Section 2 of the paper gives a brief review of wavelets and its use in getting low-resolution image with local features. Section 3 is about PZMs and their use in extracting global features and reconstruction capabilities. Section 4 discusses the hybrid approach of using wavelets and PZMs in fingerprint authentication system. Results and discussion about the results are presented in the section 5. Conclusions are given in section 6.

2. WAVELET TRANSFORM

Wavelet transform (WT) represents image as a sum of wavelets on different resolution levels. The power of the WT is that it offers high temporal localization for high frequencies while attempts good frequency resolution for low frequencies. Thus, WT is a good tool to extract local features of the image and thus is used to extract minutiae of the fingerprint image.

2.1. REVIEW OF WAVELET TRANSFORM

The effect of the WT is a convolution to measure the similarity between a translated and scaled version of the wavelet and the fingerprint image under analysis.

The wavelet analysis starts with a single function $\Psi(x) \in L^2(R)$, called mother wavelet, and all the other wavelets are derived *by* two simple operations of dyadic scaling and integer shifting of Ψ [2]:

$$\Psi_{ab}(x) = 2^{-a/2}\ \Psi(2^{-a} x - b)$$

Wavelet transform is a multiresolution analysis (MRA) tool. In MRA, a scaling function $\varphi(x)$ and the associated mother wavelet function $\Psi(x)$ are needed in the construction of a complete basis, and they satisfy the 2-scale difference equations:

$$\varphi(x) = \sqrt{2}\ \sum_n h(n)\ \varphi(2x-n)$$

$$\Psi(x) = \sqrt{2}\ \sum_n g(n)\Psi(2x-n)$$

where the coefficients *h(n) and g(n) satisfy*

$$g(n) = (-l)^n\, h(l-n)$$

i.e., the coefficients of *g(n)* can be extracted from *h(n)*.The discrete filters *h(n)* and *g(n)* are the quadrature mirror filters (QMF), and can be used to implement a wavelet transform instead of explicitly using a wavelet function.

Since fingerprint image is a 2D signal, the 1D case can be extended. 2D wavelets and scaling functions obtained from their 1D counterpart, as:

$$\varphi(x,y) = \varphi(x)\,\varphi(y)$$

and the dilation equation takes the form:

$$\varphi(x,y) = 2 \sum_k \sum_l h(k,l)\, \varphi(2x-k, 2y-l)$$

Since φ(x), φ(y) both satisfy the dilation equation, we also have

$$h(k,l)=h(k)h(l)$$

We can analogously construct the wavelets. However, now instead of 1 wavelet function, we have 3 wavelet functions:

$$\Psi_H(x,y) = \varphi(x)\Psi(y)$$
$$\Psi_V(x,y) = \Psi(x)\varphi(y)$$
$$\Psi_D(x,y) = \Psi(x)\,\Psi(y)$$

The corresponding dilation equations are:

$$\Psi_H(x,y) = 2 \sum_k \sum_l g_H(k,l)\, \varphi(2x-k, 2y-l)$$

$$\Psi_V(x,y) = 2 \sum_k \sum_l g_V(k,l)\, \varphi(2x-k, 2y-l)$$

$$\Psi_D(x,y) = 2 \sum_k \sum_l g_D(k,l)\, \varphi(2x-k, 2y-l)$$

where,

$$g_H(k,l)=h(k)g(l)$$
$$g_V(k,l)=g(k)h(l)$$
$$g_D(k,l)=g(k)g(l)$$

The approximation and detail coefficients are computed in a similar way:

$$f^{j}_{kl} = \int_{-\infty}^{\infty} 2^{j}\, \varphi(2^{j} x - k, 2^{j} y-l)\, f(x,y)\, dx\, dy$$

$$d^{(S)j}_{kl} = \int_{-\infty}^{\infty} 2^{j}\, \Psi(2^{j} x - k, 2^{j} y-l)\, f(x,y)\, dx\, dy$$

2.2 FINGERPRINT IMAGES IN WAVELET DOMAIN

In this paper, discrete wavelet transform (DWT) is used to decompose the fingerprint image into a multiresolution representation in order to keep the least coefficients possible without losing useful image information. Figure 2.2(a) shows the decomposition process by applying 2D DWT on an image, and figure 2.2(b) shows 2D DWT upto 3rd level [3].

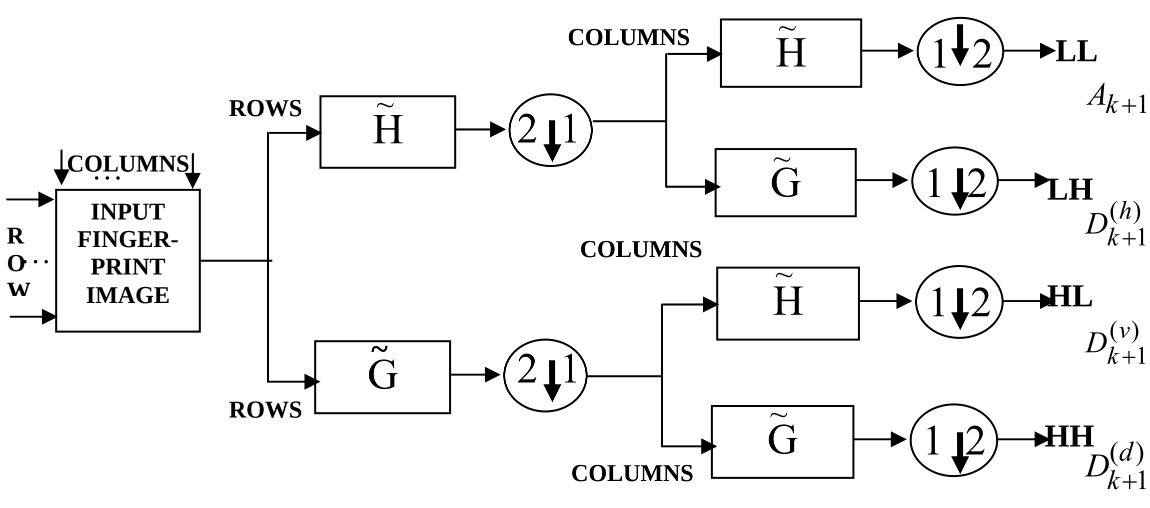

Figure 2.2(a): **2D DWT image decomposition process**

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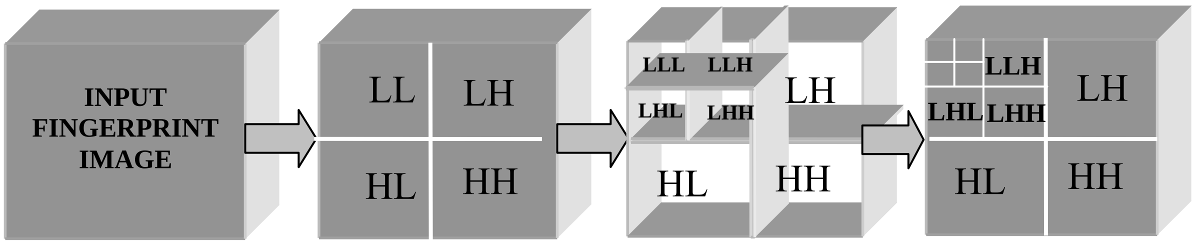

Figure 2.2(b): **2D DWT of an image at level-3**

A significant property of the wavelet transform is its ability to characterize the local regularity of functions. For example, for a fingerprint image f(x, y), edges correspond to the singularities of f(x, y), and thus are related to the local maxima of the wavelet transform modulus. Therefore, the wavelet transform is a good tool for edge detection. For a fingerprint image, the approximation coefficients, A_k, are kept zero, and the detail coefficients – $D_k^{(h)}$, $D_k^{(v)}$, and $D_k^{(d)}$ – are combined to detect the edges of the fingerprint image.

3. PSEUDO ZERNIKE MOMENTS (PZMs)

Feature extraction tool plays an important role in AFIS. We have taken PZM as a feature extractor, since it has a zero value of redundancy measure in a moment set and a higher degree of information content [4]. That's why it is an effective feature extractor even in the case of a noisy fingerprint image.

3.1. REVIEW OF PZMs

The kernel of PZMs is the set of orthogonal pseudo Zernike polynomials defined over the polar coordinates inside a unit circle. The 2D PZM of order *p* and repetition *q* of a digital image *f(x,y)* is defined as [4]:

$$PZ_{pq} = ((p+1)/\Pi) \sum_x \sum_y f(x,y) V_{pq}(r,\theta) \qquad x^2+y^2 \leq 1$$

where Zernike polynomials $V_{pq}(r,\theta)$ are defined as:

$$V_{pq}(r,\theta) = R_{pq}(r)\exp(-jq\theta) ; \qquad j=\sqrt{-1}$$

and $R_{pq}(r)$, the real-valued radial polynomials of PZMs, are defined as

$$R_{pq}(r)= \Sigma(-1)^k(p-k)!\ r^{\,p-2k} / [k!((p+|q|)/2)!((p-|q|)/2)!]$$

To compute PZMs of a fingerprint image, we take image's centre as the origin and then map the pixel coordinates to the range of the unit circle, i.e. $x^2+y^2=1$. In this process, some pixels may fall off the circumference of the circle resulting in some information loss. To overcome this, we apply the linear transformation technique (Figure 3.1) proposed by Chong *et al* [5]. This technique gives the discrete version PZMs as:

$$PZ_{pq} = \lambda(p,N) \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j)\, R_{pq}(r_{ij})\, e^{-jq\theta}$$

where,

$\lambda(p,N)=2(p+1)/[\Pi(N-1)^2]$;

$r_{ij} = x_i^2 + y_j^2$;

$\theta= \tan^{-1}(y_j/x_j)$;

$x_i = C_1 i + C_2$; $y_j = C_1 j + C_2$;

$C_1=\sqrt{2}/(N-1)$;

$C_2=-1/\sqrt{2}$

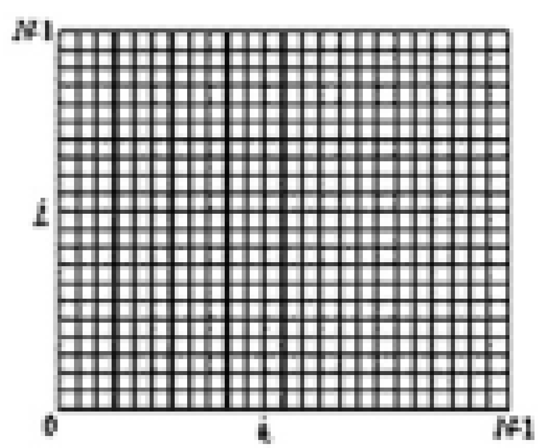

Fig 3.1(a) **Discrete image coordinate**

space of size NxN

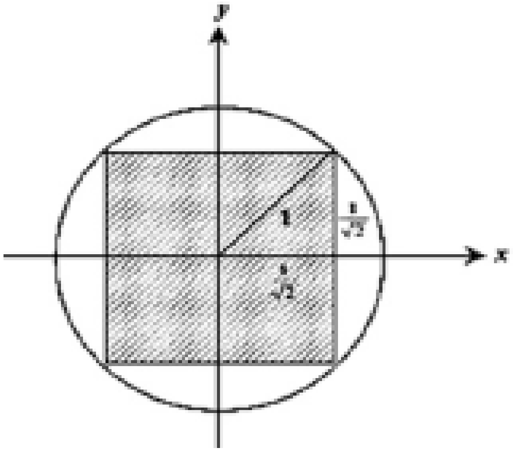

Fig 3(b) **Normalized image cordinate using the mapping** (0, N-1) -> (-1/√2, 1/√2)

4. WT AND PZMs FINGERPRINT AUTHENTICATION SYSTEM

Applying WT on the fingerprint image results in a image with lower-resolution and lesser noise. This lessens the PZMs feature extraction load and incrementing the processing time. We took fingerprint images of size 300x300 applied WT on them. We performed only two levels of wavelet decomposition because higher levels of decomposition result image with coarse resolution that is unable to provide the finer details to represent the original image. Then, PZMs are applied to extract important features.

Our fingerprint verification system comprises of two modules: enrollment and verification. Both modules have 2 sub-modules: WT-based edge detection and noise reduction, and PZM-based feature extraction. Verification phase has an extra sub-module, classification, to find out whether enrolled fingerprint and stored fingerprint are similar or not. Figure 4 shows the fingerprint authentication system block diagram

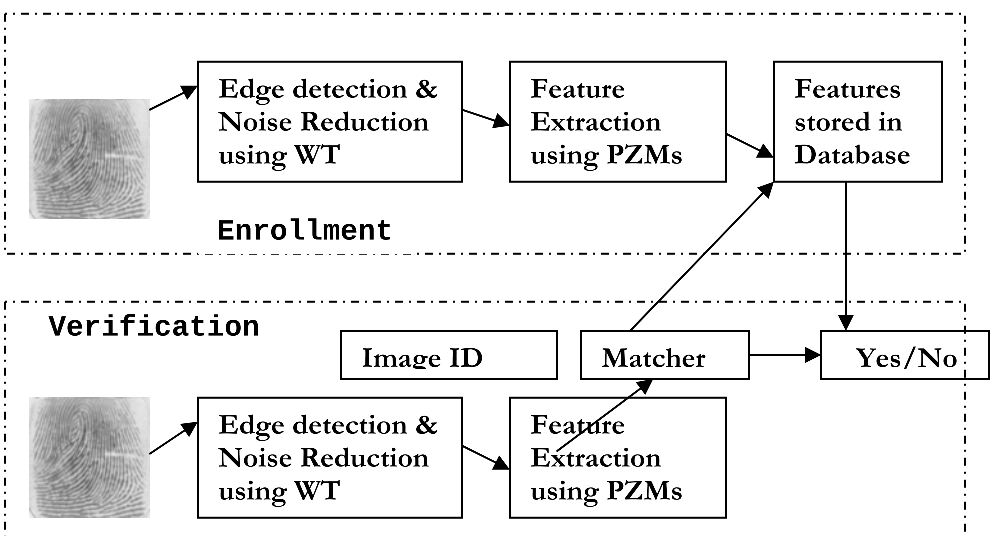

Fig 4 **Block diagram of the proposed approach**

At the enrollment stage, a set of the template images, after edge-detection/noise-removal using WT and features-extracted using PZMs, are labeled and stored into a database. At the verification stage, an input image is again processed in the same manner and after feature-extraction, is matched with the template fingerprint images stored in the database. The matcher computes the dissimilarity measure between both the images using Euclidean distance metric. This dissimilarity measure is compared to a predefined value (threshold) to determine whether a user should be accepted or rejected. If the dissimilarity measure is below the threshold, the input fingerprint is verified to have the same identity as the template fingerprint and the user is accepted.

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5. DATA COLLECTION AND EXPERIMENTAL RESULTS

5.1 DATA COLLECTION

The data for the experiment have been taken from a set of FVC2000 DB1 database which possess 10 distinct fingerprints, with 8 different versions for each fingerprint. These eight versions of each type of fingerprint vary in position and rotation. Thus a total of 80 fingerprint images were used for the experiment. For each fingerprint image, the first, third, fifth and seventh image were used for storing templates in the database, and the rest for testing the user's identity. The size of each fingerprint is 300x300, which is reduced to a size of 256x256 by using the **resize** function of MATLAB. This is done because wavelets work well on the images which are a power of 2. A few fingerprint samples from 101_n.tif category are shown in Figure 5.1(a).

101_2.tif 101_5.tif 101_6.tif 101_7.tif

Fig 5.1(a) **Some sample fingerprints from FVC2000 DB1 database**

An experiment was conducted using different settings of feature vectors based on the order of PZMs to determine the moments that maximally extract the fingerprint features. The recognition rate is shown in Figure 5.1(b). The figure shows that PZMs of order forty to forty five, which obtain the highest recognition rate, extract the best features from the fingerprint image. So, we select PZMs of order forty two for our experiments. It is also obvious from the result that higher order PZMs can extract finer details out of the image but for our purposes the pseudo zernike moments of order forty two are enough to extract features so that the fingerprint image, if reconstructed, can retain its ridgelines as it were in the original fingerprint image.

5.2 EXPERIMENTAL RESULTS

PZMs of order 40 to 45 were tested with three types of wavelet filters for extracting features of the fingerprint images - Haar, Daubechies and Symmlet filter. Total success rate (TSR) of all the filters are shown in Table 1, which indicate that the verification rate of the proposed method is highest with Symmlet wavelet filter of order 8 which accepts false fingerprint images at the rate of 4.21%, and rejects the true fingerprint image at the rate of 4.29% and verifies 95.79% fingerprint images correctly. The table also shows that the level-2 decomposition of the wavelet filters is better than level-3 decomposition. Thus excessive downsampling process gets rid of the ridge line structures of the coarser images, and degrades the feature extraction through PZMs.

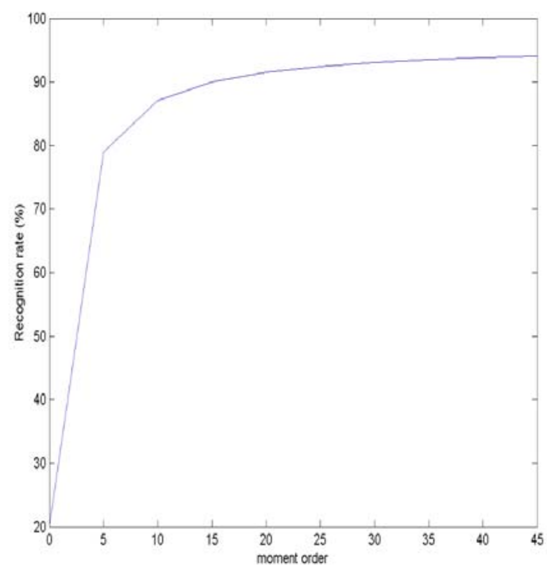

Fig 5.1(b) Plot of Recognition rate Vs Moment-order

No.	Filter	Decomposition Level	FAR(%)	FRR(%)	TSR(%)
1	Haar	2	5.30	5.26	94.72
		3	5.32	5.30	94.75
2	Db5	2	5.27	5.23	94.73
		3	4.92	5.00	95.08
3	Db6	2	4.76	4.77	95.22
		3	5.73	5.91	94.26
4	Db7	2	4.50	4.77	95.49
		3	6.81	6.82	93.19
5	Db8	2	4.59	4.55	95.42
		3	6.09	5.91	93.91
6	Db9	2	4.63	4.77	95.37
		3	5.12	5.68	94.48
7	Db10	2	4.55	4.55	95.45
		3	5.70	5.91	94.30
8	Sym5	2	4.52	4.54	95.48
		3	4.68	4.77	95.31
9	Sym6	2	4.56	4.55	95.44
		3	5.27	5.45	94.73
10	Sym7	2	4.83	4.77	95.18
		3	5.95	5.91	94.05
11	Sym8	2	4.21	4.29	95.79
		3	5.91	6.14	94.09

Table-1: **Verification performance of proposed method**

6. CONCLUDING REMARKS

The proposed method tries to make the best of wavelet transforms and PZMs. The ability of WT to denoise, extract ridges, and producing low-resolution fingerprint image is utilized and then the denoised and low-resolution fingerprint image is fed to PZMs to extract features. The input fingerprint image is first decomposed into a lower-resolution subband images through wavelet transformation. This transformation not only denoises and detect ridges in a fingerprint image, but also reduces the computational hard work, by using the subband image having lower resolution than the original input image. This improves computational speed by a considerable amount. The reduced-resolution denoised fingerprint image with ridges is then fed to PZMs to extract its features. In the paper, the relationship between the order of PZMs and the accuracy rate is also depicted. The higher is the order of PZMs, the more descriptive information they carry about the fingerprint image. For our purpose, PZMs of order 40 to 45 are good at extracting features from the fingerprint image. The performance of the verification after extracting features using the proposed method is 95.79%. In future, we are experimenting with wave atoms to denoise the fingerprint image in order to enhance its quality more than wavelets can, and then the verification rate can be improved.

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