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EFFICIENT FINGERPRINT RECOGNITION USING WAVELET TRANSFORMS

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Abstract- Fingerprints have long been used as a reliable biometric feature for private identification. Fingerprint classification refers to the matter of assignment fingerprints to 1 of many pre specified categories. Automatic classification may be used as a pre-processing step for fingerprint matching, reducing matching time and complexness by narrowing the search area to a set of a usually large info. Automatic fingerprint identification is one among the foremost vital biometric technologies. so as to expeditiously match fingerprints during a massive info, Associate in Nursing classification theme is critical. Fingerprint classification, that refers to assignment a fingerprint image into variety of pre-specified categories, provides a possible classification mechanism. In observe, but massive intra-class and tiny interclass variations in world pattern configuration and poor quality of fingerprint pictures build the classification drawback terribly tough. A fingerprint classification algorithmic program needs a sturdy feature extractor that ought to be ready to reliable extract salient options from input pictures.

Keywords: Fingerprints, algorithmic, fingerprint identification, wavelet transforms.

I. INTRODUCTION

As probably the most fashionable biometric qualities, fingerprints are commonly utilized in personal authentication, peculiarly with the supply of a sort of fingerprint acquisition instruments and the advent of thousands of advanced fingerprint realization algorithms. Such algorithms make use of uncommon fingerprint features that can most commonly be categorised at three levels of detail [1], as shown in Fig. 1 and known as degree 1, level 2, and degree 3. Degree-1 points are the macro details of fingerprints, equivalent to singular elements and world ridge patterns, e.g., deltas and cores (indicated by way of crimson triangles in Fig. 1). They aren't very individual and are accordingly most often used for fingerprint classification alternatively than recognition.

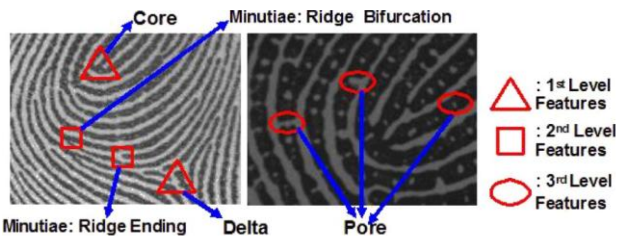


Fig. 1. Three levels of fingerprint features.

The level-2 facets (red rectangles) primarily consult with the Galton features or minutiae, particularly, ridge endings and bifurcations. Degree-2 features are probably the most distinguished and stable features, which might be utilized in almost all automated fingerprint consciousness systems (AFRSs) [1]–[3] and might reliably be extracted from low-resolution fingerprint pictures (~500 dpi). A decision of 500 dpi can also be the usual fingerprint resolution of the Federal Bureau of Investigation for AFRSs using minutiae. Level-3 aspects (crimson circles) are often outlined because the dimensional attributes of the ridges and incorporate sweat pores, ridge contours, and ridge area points, all of which provide quantitative data supporting more correct and robust fingerprint realization. Among these facets, pores have most broadly been studied [4]–[17] and are viewed to be reliably to be had simplest at a resolution greater than 500 dpi.

Decision is without doubt one of the essential parameters affecting the best of a digital fingerprint picture and so, it has an essential function in the design and deployment of AFRSs and influences each their fee and consciousness efficiency. Despite this, the area of AFRS does now not presently have a good-verified reference decision or regular resolution for top-decision AFRS that can be used interoperable between extraordinary AFRSs. For illustration, Stosz and Alyea extracted pores at a resolution of roughly 1270 dpi in the vertical direction and 2400 dpi in the horizontal direction (1270 dpi × 2400 dpi) [5]. Jain et al. chose a resolution of 1,000 dpi based on the 2005 ANSI/NIST fingerprint commonplace update workshop [4]. The Committee to define a multiplied Fingerprint characteristic Set [12] defined degree-three features at a decision of a thousand dpi. Zhao et al. Proposed some pore extraction and matching ways at a resolution of 902 dpi × 1200 dpi [9]–[11]. Finally, the international Biometric crew analyzed stage-three facets at a decision of 2000 dpi [13].

II. PROPOSED WORK

This section suggests the proposed procedure which includes two primary modules as shown in Fig. 8 which represents the methodology of the implementation. The whole fingerprint identification process entails enrollment module and identification module. Enrollment module entails the storage of fingerprint photographs into database, even as the identification module tactics the input fingerprint image, compares it with the fingerprint snap shots from database and matches it to the proper fingerprint snapshot from database. Each of the enrollment module and identification module has characteristic extraction approach. In this procedure, after finding the core point of the fingerprint snapshot, neighborhood of interest (ROI) is extracted round this core point with the intention to make the method translation invariant. After that follow multilevel wavelet decomposition on the extracted ROI. At every level, the wavelet change into decompose the given picture into three directional components, i.e. Horizontal, diagonal and vertical element sub bands within the direction of zero, forty five and 135 respectively aside from the approximation (or) gentle sub band. At each stage and in each and every course wavelet signatures are acquired as feature set for the realization rationale.

Fig. 8 Proposed methodologies for Fingerprint identification.

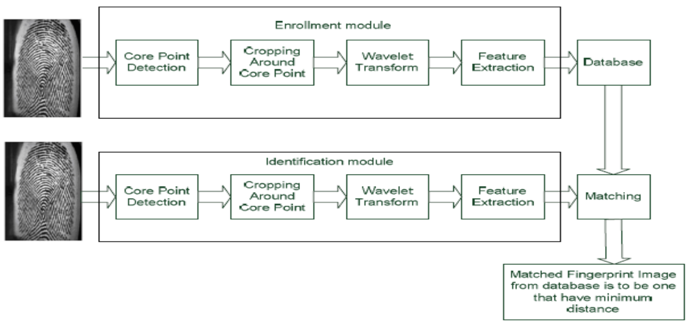


Fig2 Proposed methodology for Fingerprint identification

In [30], conjectures that the feel can also be characterized with the aid of the statistics of the wavelet detail coefficients and accordingly introduces wavelet signatures as feature set as shown under: Wavelet Signatures:

Energy Signatures: The wavelet power signatures replicate the distribution of vigour along the frequency axis over scale and orientation and have tested to be very robust for texture characterization. Vigour signatures are defined as

$$E_{ni} = \frac{1}{N}\sum_{j,K}\left(D_{ni}(b_j, b_K)\right)^2$$

Where N is the total number of coefficients, D_{ni} is decomposed image at level n and in a direction i (horizontal, vertical and diagonal). Histogram Signatures: It captures all first order statistics using a model based approach from the detail histogram ($h_{ni}(u)$) where n is the level of decomposition and i is the direction (horizontal, vertical and diagonal) of decomposition. The detail histogram of the natural textured images can be modeled as a family of exponentials.

$$h(u) = ke^{-(|u|/\alpha)^{\beta}}$$

Where α and β are wavelet histogram signatures, which are easily interpreted as specific, independent characteristics of the detail histogram.

Co-occurrence Signatures: It reflects the second order statistics of the coefficients. The element (j, k) of the co-occurrence matrix $C_{ni}^{\delta\theta}$is defined as the joint probability that a wavelet coefficient D_{ni} = j co-occurs with coefficient D_{ni} = k on a distance δ in direction θ. Formulas for eight fashioned co-prevalence features are offered in [30]. These facets extracted from the element photos are known as the wavelet concurrence signatures. In [32] proposed that the combine use of rotated wavelet filter (RWF) and discrete wavelet

develop into (DWT) centered texture facets raises the feel attention premiums. So the usage of RWF and DWT headquartered fingerprint texture points (Wavelet Signatures) can be used to expand the fingerprint attention rates.
All these texture aspects involve the characteristics of the fingerprint snapshot and it could characterize the fingerprint photograph. This texture feature is when compared and matched with the texture characteristic of pictures from database. The matched fingerprint photograph from database is the one who have minimal distance worth. For the matching of database template and experiment template aspects distinctive distance metrics can be used like Euclidean distance, Canberra distance, and Manhattan Distance metrics.

III. COMPUTATION OF THE INTER-FINGERPRINT SIMILARITIES

As a official fingerprint examiner depends generally on minute details of ridge buildings, our strategy for inter-fingerprint similarity computation is based on the topological structural matching of trivia. Fig. 2 indicates the system of the inter-fingerprint similarity computation. It includes preprocessing, characteristic extraction, and feature matching. The preprocessing element objectives to siphon the helpful parts for fingerprint awareness whilst cast off non-fingerprint components from fingerprint pics. Then, through the characteristic extraction component, each fingerprint is represented as a collection of parameters. Subsequently, via analyzing the parameters of fingerprints in pairs, the feature matching component compares the similarities of the fingerprints. Note that since there had been countless studies investigating the problem of measuring the similarities between fingerprints, this paper does now not goal to propose revolutionary options.

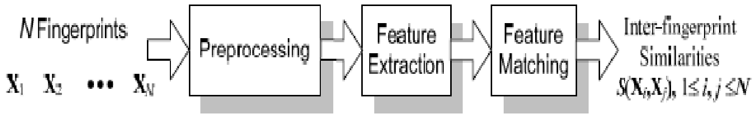


Fig. 2. Procedure of the inter-fingerprint similarity computation.

IV. GENERATION OF CLUSTERS

After computing the inter-fingerprint similarities, the next step is to assign the fingerprints
Deemed similar to each other to the same cluster. This is done by an agglomerative
Hierarchical clustering method [23], which consists of the following procedure:

1. Begin initialize M N, and form clusters c_i $\{X_i\}$, i = 1, 2, . . . , N
2. do
3. find the most similar pair of clusters, say c_i and c_j
4. merge c_i and c_j
5. M M-1
6. until M = 1
7. end

The similarities between a pair of clusters say c_i and c_j can be derived from the inter fingerprint similarities, according to one of the following heuristic measures:

(i) Complete linkage

$$S_c(c_i, c_j) = \min_{X_n \in c_{i,} X_k \in c_j} S(X_n, X_k)$$

(ii) Single linkage

$$S_c(c_i, c_j) = \max_{X_n \in c_{i,} X_k \in c_j} S(X_n, X_k)$$

(iii) Average linkage

$$S_c(c_i, c_j) = \frac{1}{\#(X_n \in c_i, X_k \in c_j)} \sum_{X_n \in c_{i,} X_k \in c_j} S(X_n, X_k)$$

Where $\#(X_n \in c_i, X_k \in c_j)$ denotes the number of fingerprint pairs in the summation.

V. FINGERPRINT CLASSIFICATION

1. Fingerprint Alignments.

Considering the interpretation and rotation between template photographs and probe photographs, this paper adopted the algorithm in [14] to accomplish the fingerprint picture registration. The algorithm used the reference facets of the vital area to calculate the parameters of translation and rotation, which is far more basic when there aren't any cores in the fingerprint snap shots.

2. Fast Discrete Curve let transform (FDCT).

Curvelets were proposed by Candese and Donoho, constituting a family of frames that are designed to represent the edges and other singularities along curves. Conceptually, the Curve let transform is a multiscale pyramid with many orientations and positions at each length scale and needle-shaped elements at fine scale. This pyramid is nonstandard, however. Indeed, Curvelets have useful geometric features that set them apart from wavelets and the likes. For instance, Curvelets present highly anisotropic behavior as it has both variable length and width. At fine scale, anisotropy increases with decreasing scale, in keeping with power law.

In 2006, Cand`es et al. proposed two fast discrete Curve let transforms (FDCT).The first one is based on unequally spaced fast Fourier transforms (USFFT), and the other is based on the wrapping of specially selected Fourier samples (FDCT WARPING). Curvelets by warping have been used for this work, because this is the fastest Curve let transform currently available [16].

After Curve let transform, several groups of Curve let coefficients are generated at different scales and angles. Curve let coefficients at scale j and angle l are represented by a matrix$C_{j,l}$, and scale j is from finest to coarsest scale, and angle l starts at the top-left corner and increases clockwise.

Suppose that $f(t_1, t_2)$, 1 t_1 N_1, 1 t_2 N_2 denotes original image and $\hat{f}[n_1, n_2]$ denotes 2D discrete Fourier transform; N_1, N_2 is the size of original image. The implementation of FDCT WARPING is as follows.

Step 1. 2D FFT (fast Fourier transform) is applied on $f(t_1, t_2)$ to obtain Fourier samples $\hat{f}[n_1, n_2]$.

Step 2. Resample $\hat{f}[n_1, n_2]$ at each pair of scale and direction j, l in frequency domain, yielding the new sampling function:

$$s\hat{f}[n_1, n_2 - n_1 tan\theta_l], (n_1, n_2) \in P_j$$

where $P_j = \{(n_1, n_2),\ n_{1,0} \le n_1 < n_{1,0} + L_{1,j}, n_{2,0} \le n_2 < n_{2,0} + L_{2,j}\}$ and $n_{1,0}$ and $n_{2,0}$ are two initial positions of the window function $\tilde{u}_{j,l}[n_1, n_2\ ]$.

$L_{1,j}$ and $L_{2,j}$ are relevant parameters of 2^j and $2^{j/2}$, respectively, and they are length and width components of window function support interval.

Step 3. Multiplication of the new sampling function$\hat{f}[n_1, n_2 - n_1 tan\theta_l]$ with window function $\tilde{u}_{j,l}[n_1, n_2]$, and the result is [16]

$\tilde{f}_{j,l}[n_1, n_2],\ = \hat{f}[n_1, n_2 - n_1 tan\theta_l]\tilde{u}_{j,l}[n_1, n_2]$

Where

$\tilde{u}_{j,l}[n_1, n_2]= w_j(w_1, w_2)v_j\left(s_{\theta_l}.\frac{(2^{\lfloor j/2\rfloor}w_2)}{w_1}\right)$,

$$w_j(w_1, w_2) = \sqrt{\emptyset_{j+1}^2(w^2) - \emptyset_j^2(w^2)}$$

$$\emptyset_j(w_1, w_2) = \emptyset(2^{-j}w_1)\emptyset(2^{-j}w_2)$$

$$s_{\theta_l} = \begin{bmatrix} 1 & 0 \\ -tan\theta_l & 1 \end{bmatrix}$$

$$tan\theta_l = l \times 2^{\lfloor -j/2\rfloor}, l = -2^{\lfloor -j/2\rfloor}, \ldots\ldots, 2^{\lfloor -j/2\rfloor} - 1$$

Step 4. Apply the inverse 2DFFT to each$\tilde{f}_{j,l}$, hence collecting the discrete coefficients$C_{j,l}$.

VI. RELATED WORK

Lin Zhang Wu et al., 2010 [21] In this research paper Biometric based personal authentication is an effective method for automatically recognizing, with a high confidence, a person’s identity. By observing that the texture pattern produced by bending the finger knuckle is highly distinctive, in this paper they present a new biometric authentication system using finger-knuckle-print (FKP) imaging. A specific data acquisition device is constructed to capture the FKP images, and then an efficient FKP recognition algorithm is presented to process the acquired data in real time. The local convex direction map of the FKP image is extracted based on which a local coordinate system is established to align the images and a region of interest is cropped for feature extraction. For matching two FKPs, a feature extraction scheme which combines orientation and magnitude information extracted by Gabor filtering is proposed. An FKP database, which consists of 7,920 images from 660 different fingers, is established to verify the efficacy of the proposed system and promising results are obtained. Compared with the other existing finger-back surface based biometric systems, the proposed FKP system achieves much higher recognition rate and it works in real time. It provides a practical solution to finger-back surface based biometric systems and has great potentials for commercial applications.

Choonwoo Ryu et al., 2011 [22] This paper presents a stochastic resonance approach for enhancing feature extraction from low-quality fingerprint images. Fingerprint feature extraction is improved by adding Gaussian noise to the original low-quality fingerprint images that were rejected by feature extractors. With the FVC2004 DB2 database and the VeriFinger fingerprint verification algorithm, eleven fingerprint images fail in feature extraction due to poor sensing conditions, i.e., dry or wet sample fingerprint images. Nine images are rejected by poor fingerprint patterns with severe wrinkles or cracks. The SR enhancement enables feature extraction of 10 images out of 11 low-quality fingerprint images. However, no feature extraction was possible from nine damaged fingerprint images. In terms of matching performances, the equal error rate is improved from 6.55% to 5.03%, and the ROC curve shows that genuine acceptance rates are improved for all false acceptance rates.

Javier Galbally et al., 2011 [23] The vulnerabilities of fingerprint-based recognition systems to direct attacks with and without the cooperation of the user are studied. Two different systems, one minutiae-based and one ridge feature-based, are evaluated on a database of real and fake fingerprints. Based on the fingerprint images quality and on the results achieved on different operational scenarios, we obtain a number of statistically significant observations regarding the robustness of the systems.

Zin Mar Win et al., 2011 [24] The fingerprint recognition system for the low quality images is presented in this paper. The recognition processes are performed among the current good quality image (device image) and other low quality images (ink image, NRC card). The proposed approach is very simple compared to minutia point pattern matching algorithm. Because we apply the Gabor filtering to enhance the fingerprint before doing other processing steps, the proposed system can identify not only the fingerprint image from device but also the low quality image on printed paper. The effectiveness of the proposed approach can be confirmed through the experimental results with acceptable errors.

Marina Blanton et al., 2011 [25] Recent advances in biometric recognition and the increasing use of biometric data prompt significant privacy challenges associated with the possible misuse, loss or theft, of biometric data. Biometric matching is often performed by two mutually suspicious parties, one of which holds one biometric image while the other owns a possibly large biometric collection. Due to privacy and liability considerations, neither party is willing to share its data. This gives rise to the need to develop secure computation techniques over biometric data where no information is revealed to the parties except the outcome of the comparison or search. To address the problem, in this work we develop and implement the first privacy-preserving identification protocol for iris codes. We also design and implement a secure protocol for fingerprint identification based on Finger Codes with a substantial improvement in the performance compared to existing solutions. We show that new techniques and optimizations employed in this work allow us to achieve particularly efficient protocols suitable for large data sets and obtain notable performance gain compared to the state-of-the-art prior work.

David Zhang et al., 2011 [26] This paper has proposed a method for selecting a reference resolution for use in high-resolution AFRSs based on minutiae and pores. We have initially found that, based on anatomical evidence, a minimum resolution of 700 dpi would give good results, but further analysis based upon an analysis of the number of minutiae and pores and the ridge width on different kinds of fingers and on fingers of different genders, as well as tests of comparative accuracy, has led us to recommend a reference resolution of 800 dpi. While we have regarded this as an advance, we must point out that the image size also has an important role in high-resolution AFRSs. In this paper, we limited images to a size of 380 × 360 pixels to allow us to investigate only the impact of resolution. In future work, we will investigate how to best make the tradeoff between the influences of resolution and image size within a certain range on high-resolution AFRS and to figure out whether there exists a dynamic resolution to different image sizes for high-resolution AFRSs.

Yi Wang et al., 2011 [27] Identifying incomplete or partial fingerprints from a large fingerprint database remains a difficult challenge today. Existing studies on partial fingerprints focus on one-to-one matching using local ridge details. In this paper, we investigate the problem of retrieving candidate lists for matching partial fingerprints by exploiting global topological features. Specifically, we propose an analytical approach for reconstructing the global topology representation from a partial fingerprint. Firstly, we present an inverse orientation model for describing the reconstruction problem. Then, we provide a general expression for all valid solutions to the inverse model. This allows us to preserve data fidelity in the existing segments while exploring missing structures in the unknown parts. We have further developed algorithms for estimating the missing orientation structures based on some a priori knowledge of ridge topology features. Our statistical experiments show that our proposed model-based approach can effectively reduce the number of candidates for pair-wised fingerprint matching, and thus significantly improve the system retrieval performance for partial fingerprint identification.

G. S.Badrinath et al., 2011 [28] In this research paper this paper presents a novel combination of local-local information for an efficient finger-knuckle-print (FKP) based recognition system which is robust to scale and rotation. The non-uniform brightness of the FKP due to relatively curvature surface is corrected and texture is enhanced. The local features of the enhanced FKP are extracted using the scale invariant feature transform (SIFT) and the speeded up robust features (SURF). Corresponding features of the enrolled and the query FKPs are matched using nearest-neighbor-ratio method and then the derived SIFT and SURF matching scores are fused using weighted sum rule. The proposed system is evaluated using PolyU FKP database of 7920 images for both identification mode and verification mode. It is observed that the system performs with CRR of 100% and EER of 0:215%. Further, it is evaluated against various scales and rotations of the query image and is found to be robust for query images downscaled upto 60% and for any orientation of query image.

David Zhang et al., 2011 [29] In this research paper High-resolution automated fingerprint recognition systems (AFRSs) offer higher security because they are able to make use of level-3 features, such as pores, that are not available in lower resolution (< 500-dpi) images. One of the main parameters affecting the quality of a digital fingerprint image and issues such as cost, interoperability, and performance of an AFRS is the choice of image resolution. In this paper, they identify the optimal resolution for an AFRS using the two most representative fingerprint features: minutiae and pores. They first designed a multi resolution fingerprint acquisition device to collect fingerprint images at multiple resolutions and captured fingerprints at various resolutions but at a fixed image size. They then carried out a theoretical analysis to identify the minimum required resolution for fingerprint recognition using minutiae and pores.

Rakesh Verma et al., 2011[30] In this research paper Fingerprint verification is one of the most reliable personal identification methods and it plays a very important role in forensic applications like criminal investigations, terrorist identification and National security issues. Some fingerprint identification algorithm (such as using Fast Fourier Transform (FFT), Minutiae Extraction) may require so much computation as to be impractical. Wavelet based algorithm may be the key to making a low cost fingerprint identification system. Wavelet analysis and its applications to fingerprint verification is one of the fast growing areas for research in recent year. Wavelet theory has been employed in many fields and applications, such as signal and image processing, communication systems, biomedical imaging, radar, air acoustics, theoretical mathematics, control system, and endless other areas. However, the research on applying the wavelets to pattern recognition is still too weak. As the ridge structure in a fingerprint can be viewed as an oriented texture pattern. The paper proposes a fingerprint recognition technique based on wavelet based texture pattern recognition method.

VII. RESULT AND ANALYSIS

1) Image Results

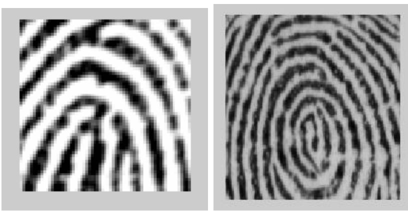
The original size of the fingerprint image is 388 x 374 pixels. Image after finding the core point is shown in figure 5.1.

Figure (a)

Figure (b)

Figure 4 (a) Original Image (b) Image after core point detection

The cropped images of size 64 x 64 pixels and 128 x 128 pixels after finding the core point is shown in figure 5.2.



Figure(a) Figure(b)

Figure 5 (a) Cropped 64 x 64 pixels image (b) Cropped 128 x 128 pixels image

The cropped 64 x 64 pixels fingerprint image is divided into four non overlapping equal parts of size 32 x 32 pixels is shown in figure 5.3.

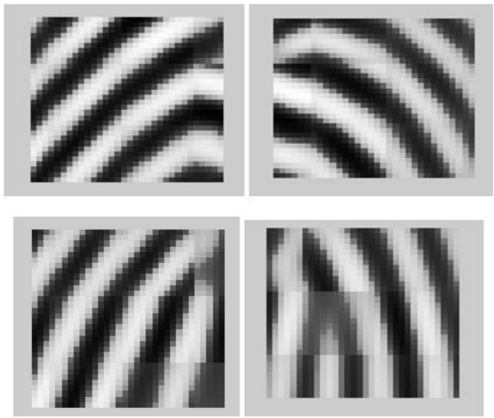


Figure 6 Four sub images of cropped fingerprint image

The image after wavelet transform contains the directive information (Horizontal, Vertical and Diagonal) is shown in figure 5.4.

2) Performance of the Fingerprint Identification System

With the intention to test the efficiency of the fingerprint identification method, fingerprint pix from database of FVC 2002 had been used. 20 fingerprint portraits have been chosen from the FVC 2002 database, the place the 20 fingerprint pictures had been from 5 peoples, four impressions had been taken from each and every individual. A whole of 5 fingerprint photos from 5 exclusive men and women had been processed and stored in database.

Accuracy price (Wavelet Co-incidence Signatures)

First the system is verified utilizing Wavelet Co-occurrence Signatures. Facts derived from co-incidence matrix are used as function set for the fingerprint attention. Right here length of feature vector is 72 (36 Homogeneity and 36 Correlation).

For the first checking out, the enter fingerprint pix had been equal because the 5 fingerprint images that saved in database. The enter fingerprint pix had been loaded into the fingerprint identification method for the verification reason. The complete of accurately matched percentage is a hundred%. Table 5.Three shows the outcome.

Table 1Result Verification in the Case when Input Images are same as the Database Images.

Input Fingerprint Images from People No.	Database Fingerprint Images from People No.					Correctness
	1	2	3	4	5	
1	M	0	0	0	0	100 %
2	0	M	0	0	0	100 %
3	0	0	M	0	0	100 %
4	0	0	0	M	0	100 %
5	0	0	0	0	M	100 %
Total Percentage of Correctness						100%

Table 2 Result Verification with Different Fingerprint Impressions that belong to the Same Person

Input Fingerprint Images from People No.	Number of Fingerprint Images	Database Fingerprint Images from People No.					Correctness
		1	2	3	4	5	
1	4	4 M	0	0	0	0	100 %
2	4	0	4 M	0	0	0	100 %
3	4	1 M	0	1 M	0	2 M	25 %
4	4	0	0	0	3 M	1 M	75 %
5	4	1 M	0	0	1 M	2 M	50%
Total Percentage of Correctness							70%

VIII. CONCLUSION

The paper proposes a fingerprint realization process situated on wavelet situated texture sample realization system. It is discovered that the directional resolving vigor of wavelets extracts the texture knowledge in Horizontal, Vertical and Diagonal guidelines of the fingerprint pics. The use of this local texture knowledge can be used to develop the efficiency price. Combine use of DWT and RWF headquartered Wavelet Signatures (energy Signatures, Histogram Signatures and Co-prevalence Signatures) can broaden the awareness charges. Wavelet situated systems don't require any preprocessing and publish processing steps so they are fast as compare to previous minutiae situated systems. Using multi-decision, compactness and de-noising property of wavelets makes it valuable in fingerprint consciousness approach..

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