

A Robust Hierarchical approach to Fingerprint matching based on Global and Local Structures

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Abstract

Among the various biometric techniques for authentication, fingerprint recognition for personal verification and identification has received considerable attention over the past decades because of the distinctiveness and persistence properties of fingerprints. Automatic matching phase is one of the main stages in fingerprint recognition. In this paper, a novel two-step hierarchical approach to fingerprint matching is proposed based on global Directional Variance Features (DVF) and local cues. At the first level, the matching reduces to finding the Euclidean distance between the DVFs of the input and stored fingerprints extracted from global characteristics and then uses the presented local structure representation based on spatial relationships between the minutiae and reference point for accurate matching at the next level. Final matching or similarity score is evaluated by combining DVF and Local Structure (LS) matching scores of the query and template fingerprints. The proposed matching system has been tested on FVC2002 databases for its accuracy and fidelity on various qualities of fingerprints and the results show a significant reduction in the Equal Error Rate (EER) and processing time when compared to other methods validated on the same database.

Keywords: Euclidean distance, Reference point, Directional variance, Ridge count, Minutiae.

INTRODUCTION

Biometrical identity authentication systems based on fingerprint analysis have been deployed in a wide range of application domains ranging from law enforcement and forensics to unlocking mobile phones because of its easy accessibility, uniqueness and reliability. Depending on the context of the application, the fingerprint authentic system may be either a verification system or an identification system. A verification system authenticates a person's identity by comparing the captured fingerprint with her/his previously enrolled fingerprint reference template [1]. An identification system recognizes an individual by searching the entire enrolment template database for a match [1]. The fingerprint feature extraction and matching algorithms are usually quite similar for both fingerprint verification and identification problems [1].

Though a large number of fingerprint matching algorithms have been proposed in the literature, matching partial and noisy fingerprints continues to be an important challenge. When a partial fingerprint does not include one or more

singular points, common matching approaches based on alignment of these structures fail. The other challenges are due to large intra-class variations in fingerprint images of the same finger and inter-class similarity between fingerprint images from different fingers. The existing matching approaches can be classified into image-based, minutiae based and non-minutiae feature based such as ridge shape, texture information etc. The image-based methods compute the correlation of the two fingerprint images to determine the similarity between them either in the spatial or frequency domain [3]-[5]. The matching algorithm proposed in [3] calculated 12 different cross correlations based on certain radius values from the reference point for both the input and stored images to determine whether the images correspond to the same fingerprint. Local correlation of regions around the minutiae was utilized to estimate the degree of similarity between two fingerprint images as in [4]. However, these methods are not robust to noise and non-linear distortions and requires the whole texture or image for matching.

Minutiae-based matching consists of finding the alignment between the template and the input minutiae feature sets that result in the maximum number of similar minutiae pairs [7-13]. A graph based fingerprint hashing algorithm was proposed in [8] for recognition using core and minutiae points. Planar graph and Delaunay triangulation algorithms were used for generating characteristic vector in [11] associated with each minutiae and a similarity coefficient was computed by comparing the characteristic vector. The proposed minutiae representation in [13] incorporated orientation information around the minutiae and Greedy algorithm was used to construct the set of similar minutiae. Though minutiae based techniques are popular and widely used, fingerprint matching based exclusively on minutiae may not be suitable for matching low-quality fingerprints thereby reduces the matching accuracy. Non-minutiae feature based matching compares fingerprints using Level 3 features (pores and ridge contours) [2], [14], [15]. Topological information on ridge patterns is utilized in ridge-based matching. A matching technique based on ridge features detected using Hough transform was presented in [14] and the matching score was based on the number of matched ridges in the input and template fingerprint. Matching schemes incorporating Level-3 features was proposed in [19][20] in conjunction with minutiae features to achieve higher matching accuracy but detection of pores is possible only in high resolution fingerprint images of over 1000 dpi. The computational complexity of many of these existing matching methods is high.

In this paper, a fingerprint matching scheme operating in two stages has been proposed that is based on representation schemes (DVF) that capture the global pattern of ridges and valleys and a novel local minutiae representation. Directional variance Features (DVF) are compact fixed length codes constructed using fingerprint orientation image and a unique reference point. A hierarchical approach is adopted in the matching process. Initially, the matching reduces to finding the Euclidean distance between the DVFs of template and input fingerprints extracted from global characteristics and then uses the local structure representation for finer matching. Local representations are constructed for those minutiae points that are at a fixed distance from the reference point for accurate matching at the second level. No priori complex global alignment is required for the proposed matching scheme, as the unique reference point detected in the input and stored fingerprint takes care of translation and the local

minutiae representations are characterized by attributes that are invariant to translation and rotation. The matching score at the second level combines the similarity score of DVFs matching and minutiae matching. The overview of the proposed fingerprint matching system is shown in Figure 1, and the each stage is explained in the following sections.

The rest of the paper is organized as follows: Section 2 presents the fingerprint preprocessing approach used in this work. Section 3 explains the global feature extraction (DVF) methodology. In section 4, the generation of suggested local features based on minutiae is described. Section 5 presents the proposed hierarchical fingerprint matching method. Experimental discussion and results are provided in section 6 and finally section 7 concludes the paper.

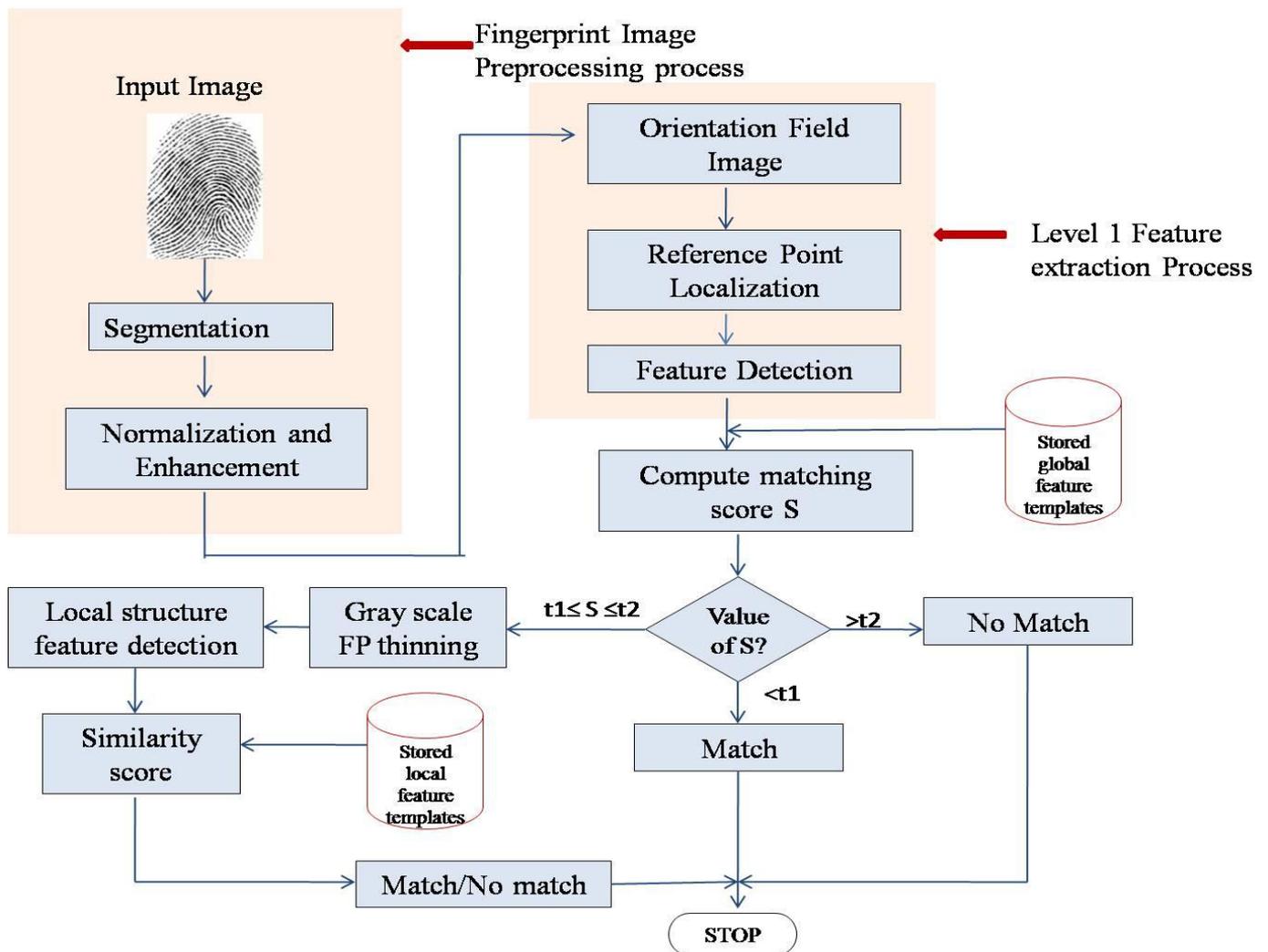


Figure 1. Block Diagram of the proposed fingerprint matching scheme

FINGERPRINT PRE-PROCESSING

Fingerprint segmentation is an essential process to isolate the foreground area that consists of an area of interest (i.e. regions of ridges and valleys of the fingerprint impression) from the background to avoid extraction of features from the background region. As foreground regions in the fingerprint image exhibit high gray-scale variance and the background exhibits very low variance, a method that is based on gray intensity variance level is used to segment the foreground from the background. The fingerprint image is then enhanced using Gaussian band pass filter in the frequency domain [21]. This is done to reduce noise and improve the legibility of the fingerprint. The process of segmentation and enhancement is carried out as described in [21].

EXTRACTING GLOBAL CHARACTERISTICS (DVF)

It is desirable to obtain fingerprint representations that are scale, translation and rotation invariant. Scale invariance is not a significant problem since most of the fingerprint images could be scaled as per the dpi specification of the sensors [2]. The main stages in the global feature extraction scheme are described below:

Orientation Field Estimation

As fingerprint Orientation Field (OF) describes the directionality of local ridge structure of a fingerprint, its estimation provides rich information for identifying global characteristics. Hence, this stage is aimed at obtaining a reliable Orientation Image (OI) (i.e. a two-dimensional matrix) whose elements encode the local orientation of the fingerprint ridges. The dominant orientation of a non-overlapping image block of size $w \times w$ is estimated by the least mean square method based on the gradients [22]. The components of the gradient g_x and g_y are determined using the classical Sobel convolution mask. The angle with maximum rate of change in gray intensity determines the directional field for that block.

As orientation field image thus computed from noisy fingerprints with poor ridge structure may contain several unreliable elements, an orientation regularization algorithm that is based on adaptively changes the smoothing neighbourhood size after analyzing the orientation consistency is used in this work as presented in [23]. A low-pass Gaussian kernel of adaptive size is convolved with the adaptive neighbourhood size block during the smoothing process. After regularization, the OF is more stable and resistant to noise for further processing.

Reference point localization using fingerprint OI

A unique reference point for subsequent feature extraction stage is detected from the orientation field image regularized using adaptive neighbourhood analysis. This point is taken as the point with maximum curvature on the convex ridge which is usually located at the central region of the fingerprint

except for partial fingerprints. This reference point localization approach is based on the hierarchical analysis of orientation coherences on varying neighbourhood [24]. The orientation consistency is low in high curvature and noisy areas than in smooth areas [24]. Multi-scale analysis of the orientation consistency is done to search the block of local minimum consistency from the largest scale to the finest scale as shown in Figure 2. Each scale is based on the outside surrounding $8 \times s$ blocks of $(2s + 1) \times (2s + 1)$ neighbourhood of the centre block and s denotes the corresponding scale of the multi-scale analysis [24]. In this work, four scales are used. Direction of curvature technique is used to determine the unique reference point.

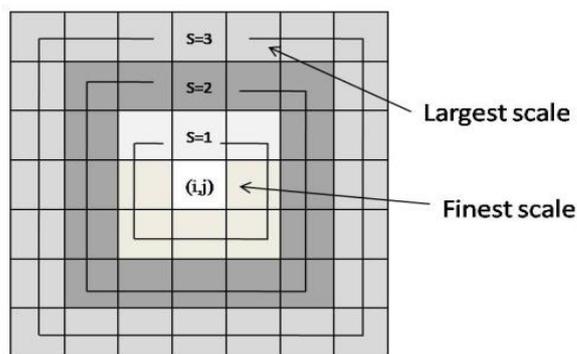


Figure 2. Multi-scale analysis of orientation consistency

This technique consistently localizes reference point accurately for all classes of fingerprints as analysed in [25].

Global Fingerprint representation

To facilitate fingerprint matching at the global level, a compact fingerprint representation, Directional Variance Features (DVF) using the orientation image and a unique reference point in the fingerprint image as proposed in [29] is used. The orientation difference between the 16 radial directions with $\pi/8$ interval as depicted in Figure 3 from the reference point and the local ridge orientations along the corresponding radial are analyzed and approximated by using the absolute sine component [24].

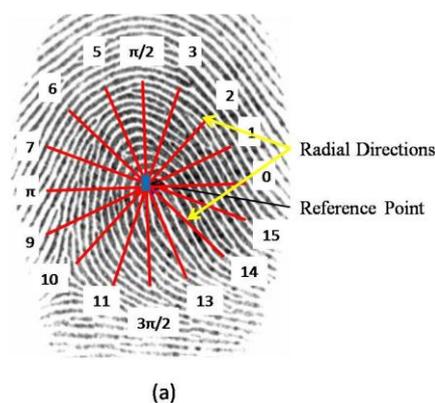


Figure 3. 16 Radial directions (0-15)[in red] with $\pi/8$ interval from the reference point [in blue]

The dominant two radial directions with two least directional variances included in the DVFs for the classification process in [29] has not been considered for the matching process as they are necessary only to establish the different predefined fingerprint classes. Hence, only the orientation pattern determined by directional variances computed from the reference point using the orientation field image along 16 radial directions ($0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ, 112.5^\circ, 135^\circ, 157.5^\circ, 180^\circ, 202.5^\circ, 225^\circ, 247.5^\circ, 270^\circ, 292.5^\circ, 315^\circ, 337.5^\circ$) constitute the feature vector to establish a match/non-match at level 1.

LOCAL STRUCTURE (LS) REPRESENTATION

Local structures around the unique reference point detected in fingerprint images are used for accurate matching at the second level. The methodology proposed in this paper for local feature extraction is based on minutiae points (ridge endings and bifurcations) and ridges. The feature extraction stages are described below:

Gray Scale Ridge Skeletonization

The common minutiae points, bifurcation and ridge end points has properties to uniquely describe a fingerprint image. A compact representation to remove redundant information as much as possible is useful to extract minutiae points. Hence, skeletonization of ridges in fingerprints becomes an essential step in the process of minutiae extraction. Extraction of reliable minutiae heavily relies on the quality of the ridge skeleton. To speed up the thinning process and to obtain reliable minutiae from fingerprint images, direct gray scale skeletonization of fingerprint ridges using parallel algorithm as proposed in [26] has been in this work. This methodology does not go through the process of binarization unlike many other thinning approaches.

Minutiae extraction Process

The widely used concept of Crossing Number (CN) defined by Rutovitz is used for extracting minutiae points in this work and is given below:

$$CN(P) = \sum_{i=1}^8 |P_i - P_{i+1}| \quad \text{with } P_9 = P_1 \quad (1)$$

For a non-zero centre pixel P , $CN(P)$ counts the number of background to non-zero transitions.

Using Eq.1 if $CN(P) = 1$, then it corresponds to a ridge point and if $CN(P) = 3$, it corresponds to ridge bifurcation.

The extracted bifurcation points and end-points in thinned fingerprint image are shown in Figure 4.

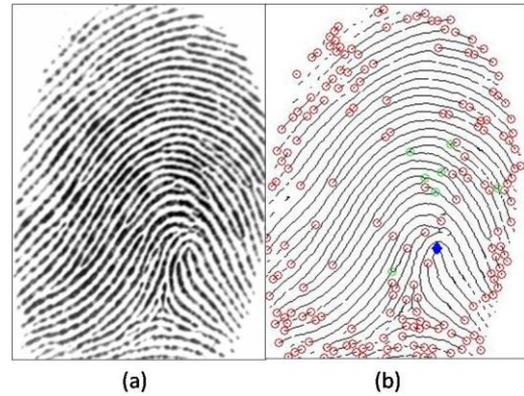


Figure 4 (a) Original FP image (b) Minutiae points ridge endings [in red] and bifurcation points [in green] extracted from the skeleton image

Feature Vector Construction

After obtaining the skeletonised ridges and minutiae information from the fingerprint images, features around the unique reference point is used to create the local feature vector. The proposed local feature extraction process for matching do not take into consideration the position of the minutiae unlike most of the conventional minutiae-based matching [11][20][30] as it becomes irrelevant when dealing with large perturbations due to rotation. Moreover, localizing a minutiae point as reference in both the input and template may also not be accurate. The components of the suggested local feature vector constructed for subsequent fingerprint matching process at the finer level exploits the fact that the Euclidean distance and spatial relationship between the reference point and a minutiae point remains constant irrespective of the fingerprint orientation as shown in Figure 5.

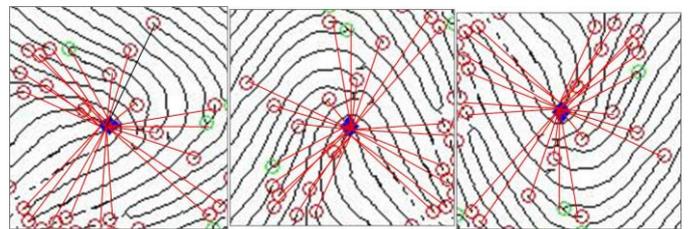


Figure 5. Interconnecting lines between reference point and minutiae points at different orientations

If we extract local features for all the minutiae in the fingerprint image, the size of the template will be very large and thereby decreases the system efficiency. Hence, only the minutiae (m_i) that are closer to the reference point (R) are selected as only 12-15 minutiae points in the input and enrolled fingerprints are enough to be matched [31]. The selection rule is based on distance function D applied on M minutiae points detected in the fingerprint image and is given by

$$|m_i - R| < D, \quad \text{where } i \in \{1, 2, \dots, M\} \quad (2)$$

The value of D is a constant that is appropriately determined experimentally.

The local characteristics recorded for each candidate minutiae m_i that satisfies Eq.(2) considered for fingerprint matching is given below :

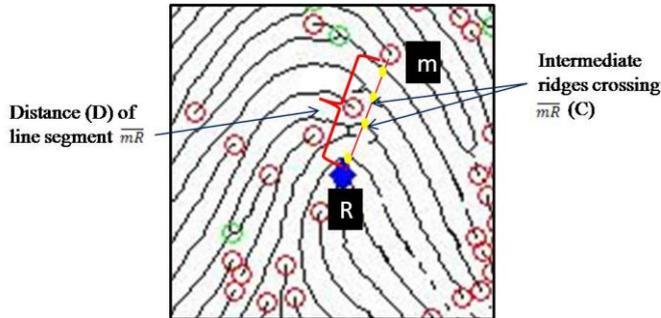


Figure 6. Local characteristics considered for each candidate minutiae

- i) **Minutiae type (T) :** The two classical types of the minutiae points are considered (i.e. ridge endings or ridge bifurcation)
- ii) **Distance or length (D):** The length of the edge connecting the minutia m_i from the reference point as shown in Figure 6. The Euclidean distance D_i between the i^{th} minutia point $m_i(a_i, b_i)$ and the reference point $R(p, q)$ is obtained from:

$$D_i = \sqrt{(a_i - p)^2 + (b_i - q)^2} \quad (3)$$

- iii) **Ridge count (C):** The number of ridges intersecting the line segment connecting the minutia point (m_i) and the reference point (R). It is determined by the number of 0 to non-zero transitions along the segment \overline{mR} of the skeleton image.

The local structure (LS) with respect to minutia(m_i) is defined as

$$LS(m_i) = (T_i, D_i, C_i)$$

where $i \in 1, 2, \dots, N$ and N is the total number of candidate minutiae.

FINGERPRINT MATCHING

The proposed hierarchical fingerprint matching algorithm works in two levels. The Euclidean distance between the DVFs of template and query fingerprints extracted from global characteristics as described in section 3 is utilized for the matching process at the initial level. Based on the decision taken in the first step, matching proceeds to the next level using the local structure representation as discussed in section 4 for finer matching.

For each finger, six templates are stored corresponding to six impressions of various image qualities that include partial and inclined fingerprints. The DVFs corresponding to each template S_i based on directional variances along 16 radial directions $[0^0, 22.5^0, 45^0, 67.5^0, \dots, 337.5^0]$ with $\pi/8$ interval is denoted as $[v_{i1}, v_{i2}, v_{i3}, v_{i4}, \dots, v_{i16}]$, where $i \in 1, 2, \dots, 6$ corresponding to six enrolled templates. Let $[q_1, q_2, q_3, q_4, \dots, q_{16}]$ denote the DVF of the input/query fingerprint I . The Euclidean distances $d(I, S_i)$ are computed between the DVFs of the input fingerprint and the six stored templates. The minimum of the six scores (\min_s) corresponds to the best alignment of the fingerprints being matched denoted by:

$$ms_{DVF}(I, S) = \min_s(d(I, S_i)) \quad (4)$$

Based on the global matching score a coarse filtering of fingerprints is made to directly determine the existence of a match and non-match using two threshold values t_1 and t_2 respectively. A score below t_1 with minimum FAR is regarded as a match and a score above t_2 is regarded as a non-match. If the computed matching score is in the range of t_1 and t_2 , fingerprint matching based on local fingerprint representations (LSs) is performed in the next level for finer matching. The match score may lie between t_1 and t_2 under the following possible scenarios:

- The input template and the stored template may be from the same finger, but the stored features are not invariant to large perturbations.
- The input and stored fingerprints are from different finger, but they are of the same class exhibiting similar directional pattern around the reference point.

Only those cases as mentioned above passes on to the next stage for finer matching and thus the overall computational complexity of the matching has been greatly reduced to a great extent. Though global characteristics may be discrete, it is not sufficient to identify fingerprints that are globally similar but with different local details, such as from twins' fingers. Hence, these fingerprints need a combination of global and local structures for accurate matching.

The second level matching is based on local features constructed for each minutia that are at a fixed distance from the reference point as described in section 4.3. Let $LS(m_i^S)$ and $LS(m_j^I)$ denote the local structure representation of a minutia, m_i^S in stored fingerprint image S and m_j^I in input image I respectively, $i = 1, 2, \dots, N^S$ and $j = 1, 2, \dots, N^I$. N^S and N^I are the total number of candidate minutiae in S and I respectively. For each $LS(m_j^I)$ in I , a matched distance (D_j^I in I and D_i^S in S) is taken as the reference between two LSs in I and S . As distortions are inevitable when mapping a three-

dimensional fingerprint onto a two-dimensional plane and also due to variations in skin conditions, a small distance error tolerance (Δt) is considered between D_j^I in I and D_i^S in S (i.e. $|D_i^S - D_j^I| < \Delta t$). If an exact match could be established between corresponding T_i^S and T_j^I , and between C_i^S and C_j^I as well, then the two LSs are considered to be a match. Similarity between two coefficient vectors representing the two fingerprints I and S is calculated according to Eq. 5.

$$MS_{LS}(I, S) = \frac{2 \times k}{(N^S + N^I) / 2} \quad (5)$$

where k is the number of matched minutiae in S and I . If sufficient number of correspondences could be made between minutiae of I and S irrespective of their orientations as shown in Figure 7, then the two fingerprint images are considered to be from the same finger.

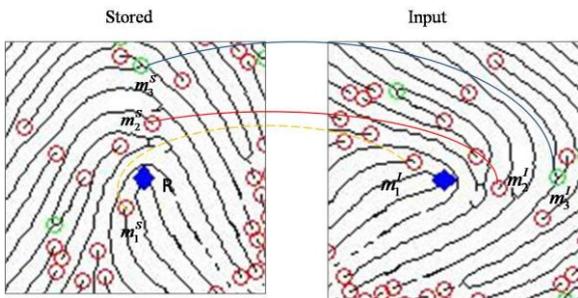


Figure 7. Local matching in the fingerprint images: projection of stored LS on the input domain

A decision using Eq.5 for a match/non-match cannot be made exclusively based on the local representations using minutiae, as detection of minutiae may not be accurate for low-quality fingerprints. Hence the similarity scores between S and I obtained from DVF matching and LS matching have been combined to derive a final matching score that is represented as follows:

$$CMS(I, S) = \frac{1}{ms_{DVF}(I, S)} \times MS_{LS}(I, S) \quad (6)$$

Higher the value of $CMS(I, S)$, greater is their similarity. The processing steps of the proposed fingerprint hierarchical matching algorithm are as follows:

Algorithm: [Hierarchical Fingerprint Matching]

Input: DVFs and LSs of S and I

Output: Match/Non-Match

- Step 1: Compute the Euclidean distances between the DVFs of the input and the stored templates.
- Step 2: Preserve the minimum of the scores \min_s that correspond to the best alignment of the input and the enrolled fingerprint.

Step 3: If the value of \min_s is less than a threshold t_1 , a correspondence between the fingerprints prevails, go to step 8, else if \min_s is greater than a threshold t_2 , a match does not exist, go to step 8.

Step 4: Given a set of local feature vectors LSs extracted from two fingerprints, $S(T_i^S, D_i^S, C_i^S)$ and $I(T_j^I, D_j^I, C_j^I)$ corresponding to minutiae m_i^S and m_j^I respectively, they are considered similar if they satisfy the following criteria

$$(|D_i^S - D_j^I| < \Delta t) \wedge (T_i^S = T_j^I) \wedge (C_i^S = C_j^I)$$

Step 5: Repeat step (4) and determine the maximum number of matched LSs corresponding to candidate minutiae in input I and stored S fingerprint images.

Step 6: Evaluate the matching score (MS_{LS}) by applying Equation 7 using local structure features.

Step 7: Finally, the matching scores obtained using DVFs and LSs are combined using Equation 8 to decide whether there exists a similarity between the input and stored fingerprint templates.

Step 8: End

RESULTS AND DISCUSSION

In this section, the recognition performance of the proposed fingerprint matching algorithm is experimentally analysed and compared with other existing approaches. Experiments have been conducted on FVC2002, Db1 and Db2 fingerprint databases, the reason being that it was acquired with an optical sensor of medium-high quality, making it suitable for evaluating algorithms to be used in civil and mobile applications. The size of the fingerprint images in Db1 and Db2 are 388 x 374 and 296 x 560 pixels respectively with 500 dpi and 256 gray levels. The images in the database are of varying qualities with creases, scars and smudges and also include partial and inclined fingerprints as well. Each database has 880 fingerprints (8 impressions from the same finger). The proposed fingerprint matching algorithm presented in this paper has been implemented in MATLAB. No rejection mechanism is used to discard fingerprint images in the database to evaluate the performance of the proposed matching algorithm.

As a two step hierarchical approach is adopted for fingerprint matching in the proposed algorithm as discussed in section 5, experimental analysis have been conducted at each level. At the first level, to establish the verification accuracy of the proposed fingerprint representation based on global characteristics and the matching approach, each impression is compared with other impressions of the same finger for genuine matches and for imposter matches, each impression is matched with all the impressions of different fingers. Hence,

for each database, 3080 genuine matchers are executed and 348,800 imposter matches are executed. The matching score in the first level is computed based on the Euclidean distance between two DVFs constructed as described in section 3.3. None of the genuine matching score is zero as images from the same finger had not generated identical DVFs because of distortions and rotation.

The decision is based on a boundary (i.e. threshold) that minimizes FAR and FRR. FAR and FRR values for different decision thresholds as a result of matches performed in this work after the initial matching step using global characteristics are shown in Table 1. When FAR is 2.3%, FRR is 2.25% and Equal Error Rate (EER) is 1.82%. The efficiency of the proposed fingerprint matching based on DVFs has been compared with the Fingercodes matching scheme as proposed in [2], and Figure 8 shows the Receiver Operating Characteristic (ROC) curves for the two matchers evaluated on FVC2002 databases.

Table 1: False Acceptance and False Rejection Rates with different threshold values for the FVC2002 DB1 and DB2 databases

Threshold value	FAR (%)	FRR (%)
0.1	0.05	19.2
0.2	0.3	4.53
0.3	1.23	2.41
0.4	2.3	2.25
0.5	3.95	1.8
0.6	23	0.1

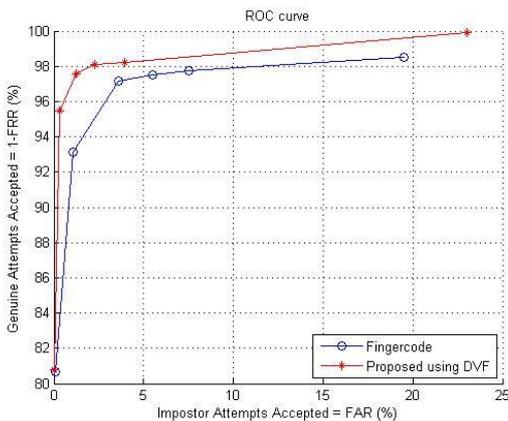


Figure 8. ROC curves of the proposed matching using DVFs and Fingercodes [2]

The basis for choosing to compare the proposed method with [2] is that it has been the most popular technique to match fingerprints based on texture information during the past decade. In [2], if the Euclidean distance between two

Fingercodes is less than a threshold, a decision is made that the two images come from the same finger, otherwise a decision that the two images come from different fingers is made. Determining the threshold is a tradeoff between the two types of errors (FAR and FRR). If a higher threshold is chosen, the genuine acceptance rate is lower, but FAR may be higher and vice versa [2].

In this proposed technique, at the first level matching, two thresholds t_1 and t_2 are chosen to determine match and non-match respectively. A decision is made that the two images come from the same finger if the match score ms_{DVF} based on the Euclidean distance of the DVFs of I and S is less than t_1 and from different fingers if greater than t_2 . Threshold t_1 is chosen with minimum FAR and threshold t_2 is chosen with sudden rise in the imposter matches. The values of t_1 and t_2 chosen are 0.1 and 0.6 respectively in this work. There is an uncertainty in the fingerprint images whose matching scores lies between t_1 and t_2 as to whether they are from the same finger or not. This is due to the fact that the stored fingerprint representation may not be invariant to large perturbations or both the input and stored templates may be from different fingers but belonging to the same class exhibiting similar pattern around the reference point as the DVFs used for matching captures more of the global pattern. It has been observed that genuine matches are high and imposter matches are low even for low-quality images and hence robust to noise.

Samples of possible fingerprints whose similarity scores (ms_{DVF}) lying between t_1 and t_2 are shown in Figure 9 and these progresses to the second level for accurate matching process. Experimental analysis on FVC2002 database for the proposed hierarchical strategy shows that, on the average 78.8 % of the fingerprints get filtered after the first level matching with either a match or non-match decision. Moreover, the feature vector (DVFs) is very compact and requires only 16 bytes irrespective of the image size.

The finer second level matching is performed based on the local structures LSs extracted from S and I as discussed in section 5. The small spatial distance threshold value Δt (1.5 in this work) is chosen after analyzing the LSs generated for various fingerprint images.

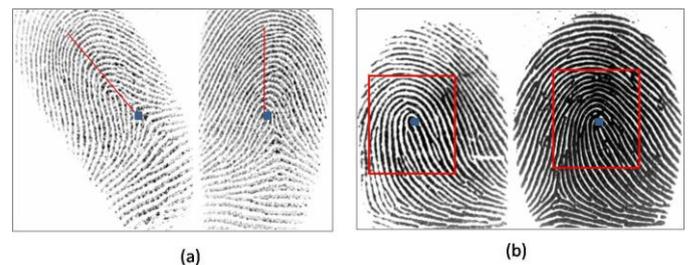


Figure 9 (a) Finger impressions belonging to the same finger (b) impressions of different fingers belonging to the same class exhibiting similar patterns around the reference point.

It has been observed that the combined matching score ($CMS(L,S)$) computed using Equation 8 based on global attributes and local structures is

- Between 1 and 2 for fingerprint images belonging to the same class but different finger.
- Less than 1 for images belonging to different class and finger.
- Between 2 and 3.5 for fingerprint images belonging to the same finger but with different orientations with large perturbations.
- Greater than 4 for same fingerprint with similar orientation.

Based on these observations the match/non-match threshold ($T=3$) has been chosen. If the similarity score is greater than T , then the decision that “the two images belong to the same finger” is made, or else a decision that “the two images originate from different fingers” is made.

Table 2 presents the EER results as recorded in the respective papers for FVC2002 databases along with the proposed matching scheme and their corresponding ROC curves is shown in Figure 10. The processing time of the proposed system is given in Table 3.

Table 2: Matching performance (EER%) of existing algorithms with proposed method

Algorithm	Feature/Structure Topology	EER(%)
Filterbank[2]	Fingercode	4.87
K-plet[28]	Minutiae-graph	1.5
Xiang[9]	Minutiae Tensor matrix(MTM)	0.8
Rodrigues [11]	Minutiae-Planar Graphics	1.14
Proposed(Stage 1)	DVF	1.6
Proposed(Stage 2)	DVF +LS(minutiae)	0.65

Table 3: Processing time of the proposed method

DVF		LS	
Feature Extraction	Matching (1:1)	Feature Extraction	Matching (1:1)
0.0354	0.0035	0.9381	0.0443

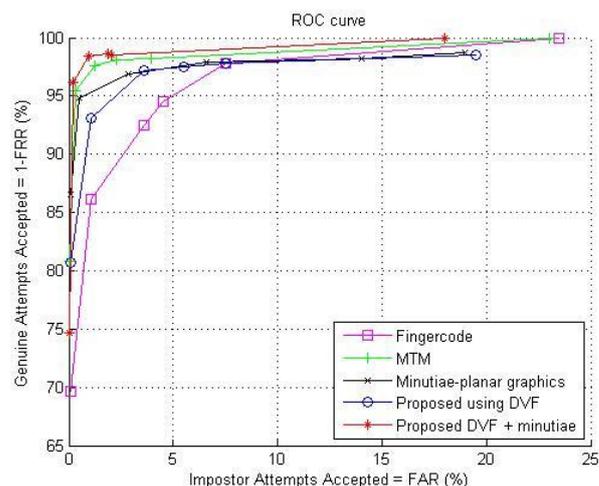


Figure 10. Comparison of the proposed method along with existing methods using ROC curves for FVC2002 database

CONCLUSION

The proposed hierarchical matching algorithms have used features based on global characteristics (DVF) that exhibit high distinctiveness among different classes and local structure matching (LS) that can tolerate high rotation distortions. Experimental results show that the overall accuracy of the proposed matching system by combining results of independent matchers based on DVF and LS fingerprint representations has significantly improved (EER 0.654%). The developed matching system can be deployed to control physical device access by integrating fingerprint recognition into laptops, tablets, smart phones and other electronic devices that have personal and sensitive data.

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