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Recognition of high resolution fingerprint images

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ABSTRACT

Fingerprint recognition is one of the most prominent biometric identification techniques. The features of fingerprint are broadly classified into three categories namely level 1, level 2 and level 3 features. In order to increase the recognition rate here the *hierarchical matching* technique is used which allows us to use all levels of features hierarchically. The level 3 features can be observed only in 1000 dpi images. So the matching is performed on a 1000 dpi fingerprint database captured using Hamster IV fingerprint scanner. At the first level of hierarchical matching the agreement between two orientation images is tested using dot product of the images. If an image is accepted at the first level it is brought to the second level of matching where minutiae details are tested. If an image crosses this stage as accepted then the decision will be taken as genuine otherwise the image will be given to the third level. The third level extracts the level 3 features such as pores and ridge contour points using Dynamic Anisotropic Pore Model (DAPM) and Mexican hat wavelet transform respectively. For each matched minutiae the pores and ridge contour points within the associated region of that minutiae will be matched. Based on the third level of matching a person is accepted as genuine or rejected as imposter.

Introduction

Fingerprint Recognition is one of the research hotspots in Biometrics. It refers to the automated method of verifying a match between two human fingerprints. Fingerprint technology relies on the concept that no two people have identical fingerprints. A fingerprint is a series of ridges and valleys on the pads of the fingers that are formed while a person is still in uterus. Except in the case of severe injury or illness, fingerprints do not change. Fingerprint identification is popular because of the inherent ease in acquisition, the numerous sources (ten fingers) available for collection.

Fingerprinting analyzes the unique pattern on the tip of our fingers. Most one fingerprint systems analyze small unique marks on the fingerprint which are known as minutiae. Some high-resolution fingerprint systems also analyze tiny sweat pores on the fingerprint which, in the same way as minutiae, are uniquely positioned to differentiate one person from another. There are three types of fingerprint features namely level 1, level 2 and level 3 features. The level 1 features are patterns of fingerprints.

The level 2 features are known as points or the minutiae features such as bifurcation and termination. The level 3 features or shape includes pores, edge contour, breaks and creases. In order to improve the recognition rate the level 3 features are included in the recognition process here.

The next section briefly explains the research work taken so far to extract level 3 information specifically pores and the level 3 features based authentication system.

Section III tells about the proposed system and gives a short description about the pore extraction technique and ridge contour extraction technique and the hierarchical matching system used here. Section IV focuses on the implementation methodology and section V presents the experimental results and the analysis part.

There are several proposed methods available for pore extraction. *A. Roddy et. al* [2] proposed a skeleton-tracking based methods. But skeletonization is computationally expensive and very sensitive to noise. This technique is not so efficient because it works well only on good quality images. This technique is not efficient since and it worked well only on very high resolution fingerprint images of high quality. *Ray et. al.* [5] proposed an approach to extract pores from fingerprint images based on the pore model. An unitary parameter is used here to detect pores whereas the pore scales and ridge/valley width vary from one fingerprint to another fingerprint. *Jain et. al.* [6] proposed to use wavelet transform to capture location of pores. They used Mexican hat wavelet transform to extract the pores but its scale parameter is experimentally set specifically for certain datasets. Then *Parsons et. al.* [7] proposed a pore extraction model assuming that pores appear as circular objects. They used a band-pass filter to detect circle like features. But the authors didn't consider the variation of pore scales in fingerprint images. In order to overcome this limitation *Q. Zhao et. al.* [8] proposed an adaptive DoG based method. *Qijun Zhao et. al.* [9] recently proposed a dynamic model which can vary its scale and orientation parameters according to the local block's orientation and ridge period values.

For ridge contour extraction *Jain et al.* [6] suggested a technique using Mexican hat wavelet transform in 2007.

Fingerprint matching algorithms are roughly classified into 3 major categories: (i) Correlation based Matching (ii) Feature based method (iii) Filter based matching. Hybrids methods are also there which combines any two feature based matching techniques. Regarding fingerprint matching involving level 3 features *Stosz and Alyea* [1] proposed a skeletonization-based pore extraction and matching algorithm. They obtained a skeletonized binary image and extracted pores. This method is

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not effective since pores extraction will not be effective when image quality is low.

Based on the previous algorithm, *Roddy* and *Stosz* [2] later conducted an analysis of pores and presented a model to find the performance of a pore-based automated fingerprint system. *Kryszczuk et. al*. [4] studied the methods of matching fragmentary fingerprints and found that there exists a relationship between the ridge structure, minutiae and pores. *Anil K. Jain et. al*. [6] studied about Level 3 details when Level 1 or Level 2 features are similar between the template and the query. The authors proposed a matching system containing multiple levels of matching where each level utilizes features at the corresponding level. They developed extraction algorithms using Gabor filters and wavelet transform.

Proposed Work

Following these works the fingerprint matching is done here by considering two level 3 features such as pores and ridge contour. The pores are extracted here using DAPM technique and the ridge contour is extracted using wavelets. Then the matching is done using hierarchical matching method.

Pore Extraction using DAPM

Pores are anisotropic in nature which could not be captured in the earlier isotropic models. The pore model used by earlier methods is isotropic model whereas DAPM is anisotropic having two parameters to adjust: scale and orientation. The DAPM model can be defined as follows:

$$P_0(i, j) = e^{\left(-j^2/2\sigma^2\right)} \cos\left(\frac{\Pi}{3\sigma} i\right)$$
$$-3\sigma \le i, j \le 3\sigma \quad (3.1)$$

$$P_\theta(i, j) = Rot(P_0, j) = e^{\left(\frac{-\hat{j}^2}{2\sigma^2}\right)} \cos\left(\frac{\Pi}{3\sigma}\hat{i}\right) \quad (3.2)$$
$$\hat{i} = i\cos(\theta) - j\sin(\theta),$$
$$\hat{j} = i\sin(\theta) + j\cos(\theta)$$
$$-3\sigma \le i, j \le 3\sigma$$

where equation (3.1) and (3.2) refers the zero and rotated model of DAPM. Here, σ is the scale parameter which controls the pore size and calculated from the local ridge frequency. θ is the orientation parameter controlling the direction of the pore model. It can be obtained by the local ridge orientation.

Ridge contours extraction using Mexican hat Wavelet transform

Ridge contours contain valuable Level 3 information including ridge width and edge shape, and are observed to be more reliable features than pores. So the ridge contours are also extracted for the purpose of matching. The ridge contour is defined as edges of a ridge. But the traditional edge detection methods are not applicable for detecting ridge contour points. Instead, the wavelets are used to enhance the ridge contours and linearly combine them with a Gabor enhanced image to obtain enhanced ridge. The Mexican hat wavelet transform used here can be defined as follows:

$$w(s,a,b) = \frac{1}{\sqrt{s}} \int\int_{R^2} f(x,y)\phi\left(\frac{x-a}{s}, \frac{y-b}{s}\right)dxdy \quad (3.3)$$

where ‘s’ is the scaling factor. ‘a’ and ‘b’ are shifting parameters.

Hierarchical Matching

Hierarchical matching scheme applied here enables the use of an extended feature set for matching at a higher level to achieve good matching decisions. The Iterative Closest Point (ICP) algorithm is a good solution for matching level3 features because it aims to minimize the distances between points in one image to geometric entities (as opposed to points) in the other image. Moreover the ICP algorithm doesn’t require one-to-one correspondence between query and template regions. The aim, of ICP is to find a closest distance between the query and template images by finding a closest point. The closest point in a template image to another point in a query image is the one which has minimum distance from the template point than all other points in query image. The pseudo code for the ICP algorithm is presented below:

Pseudo Code :

```
set iteration index k =15;
for each iteration
  for each minutiae in the tested image
    construct an associated region for each minutiae.
    for each minutiae
      for each level3 feature
        find the closest point in the template region
        find the distance between the feature point in the tested
        minutiae and the template minutiae.
      end
      find mean sum of all closest distance
      if the difference between the mean sum of current
      iteration and the previous iteration is greater than a
      threshold
          Transform the template minutiae region so that the
          distance will be minimum
          go to next iteration
      end
    end
  end
end
```

Implementation

The implementation of fingerprint recognition consists of four main stages: (i) Image Acquisition (ii) Image Enhancement (iii) Feature Extraction (iv) Matching.

One of the most essential characteristics of a digital fingerprint image is its resolution, which indicates the number of dots or pixels per inch (ppi). In order to work with level 3 features 1000 dpi images are needed. Since there is no standard database for 1000dpi images a high resolution fingerprint database is constructed containing 320 images of 40 subjects using Hamster IV fingerprint scanner. The images are of size 508x661.

In order to ensure that the performance of the minutiae extraction algorithm will be robust with respect to the quality of input fingerprint images, an enhancement algorithm which can improve the clarity of the ridge structures is necessary. A fingerprint image enhancement algorithm receives an input fingerprint image, applies a set of intermediate steps on the input image, and finally outputs the enhanced image. The fingerprint enhancement is performed as specified in [3] with the following steps and enhancement results are shown in Figure 1.

- Normalization
- Orientation Image Estimation
- Frequency Image Estimation
- Finding Region Of Interest

- Gabor Filtering

(a) (b)

Figure 1: Image Enhancement Results (a) Input Image (b) Enhanced Image

Once the image has been enhanced the fingerprint features will be extracted. The orientation obtained during enhancement can be used as a level 1 feature. The orientation of a fingerprint image computed is shown in Figure 2.

The test cases for MEPCO fingerprint databases are given in Table 1. In hierarchical matching technique initially the agreement between the orientations of two fingerprint images will be tested using dot product. Based on their agreement a match score will be assigned. If the score is greater than a particular threshold the image will be taken for testing at next level. Otherwise the image will be rejected. The results on obtained using orientation agreement are shown in Table 2 and Table 3.

For level 2 features the minutiae points has to be extracted. For this the enhanced image is first binarized and thinned using a morphological thinning operator. Then the minutiae points will be detected using CN (Crossing Number) method is used. The definition of crossing number for a pixel *P* is given in equation (4.1).

$$CN = \frac{1}{2}\sum_{i=1}^{8} | P_i - P_{i+1} | \qquad (4.1)$$

The point is a termination if CN = 1. If CN =3 the point is a bifurcation. Then the spurious minutiae introduced during the skeletonization process will be removed. Finally the location of the minutiae and the orientation of minutiae point will be marked as the minutiae feature. The results of minutiae extraction are given in Figure 3.

At the next level the minutiae matching are performed. Initially the minutiae will be aligned by aligning their ridge structure. If the ridge similarity is greater than 0.8 then that minutiae pair will be taken as reference minutiae and the other minutiae points will be aligned according to the reference minutiae.

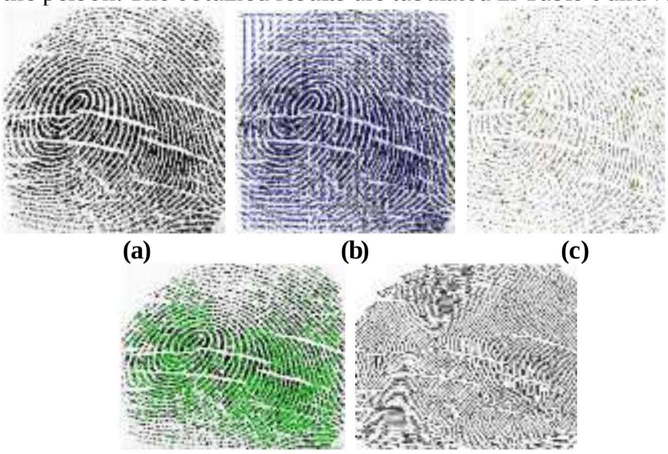
Then the distance between the minutiae at template and query images is computed. If the distance between minutiae points in the template and query images is low and if their angular distance also lies within a certain level then the minutia pair is accepted as matched. At the next the level 3 features are to be extracted. The matching result for level 2 matching is given in Table 4 and Table 5. The total number of images accepted up to level 2 matching is found by taking the no. of images rejected in level 2 matching subtracted from no. of images accepted in orientation matching.

The level 3 features used in this matching are pores and ridge contour points extracted using DAPM model and the Mexican hat wavelet transform respectively. For pore extraction initially the DAPM model is instantiated on a local block based on the local ridge orientation and ridge frequency. Then the model is used as matched filter and it is convolved with the image block.

The locations of the pores will be identified with the positions with high response. Then the spurious pores will be removed by reducing the pores lying out of ridges and the pores with size greater than 30 pixels will be removed from the feature vector. The results of pore extraction process are shown in Figure 4.

The next level 3 feature considered is ridge contour which is extracted by applying Mexican hat wavelet transform with scale factor of 1.74. The obtained response is subtracted from the Gabor enhanced image which in turn binarized with a threshold of 10. The resulting image will be convolved with a filter H [4]. The pixels of value 1-3 represent the ridge contour point in the resulting image. The results of ridge contour extraction process are shown in Figure 5.

For each matched minutiae an associated region is taken and the closest distance between the pores and ridge contour points residing inside the region is found using ICP algorithm [1]. If the distance is within 10 pixels then the minutiae pair will be taken as matched otherwise eliminate the pair. Finally the updated number of minutiae will be checked to accept or reject the person. The obtained results are tabulated in Table 6 and 7.

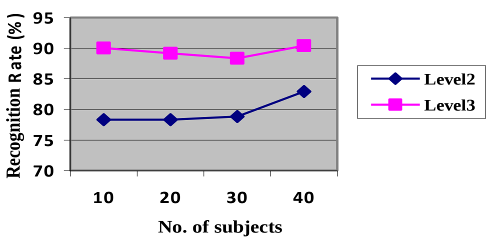


(a) (b) (c)

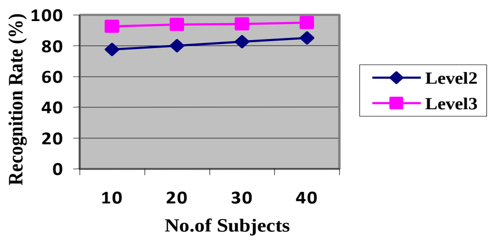
(d) (e)

Figure 2: Fingerprint Features (a) Input Image (b) level 1: Orientation Image (c) Level 2: Minutiae Points (d) and (e) Level 3: Pores and Ridge Contour Points

The tabulated results shows that the level 3 feature extraction improves the results by enabling the subjects to be accepted which are rejected in the level 2 feature matching stage. Thus it improves the Genuine Acceptance rate thereby reducing the False Rejection Rate. The total number of image accepted up to level 3 matching is found by taking the number of images rejected in level 3 matching subtracted from no. of images accepted in orientation matching. The recognition results for test cases 1 and 2 are shown graphically in Figure 3.



(a)



(b)

Figure 3: Performance Comparison of Recognition results of Level 2 matching and Level 3 matching (a) test case 1 (b) test case 2

Conclusion

The Fingerprint recognition technique is developed with the objective of improving the recognition results by including extended feature set (pores and ridge contour) in the matching process. The pores are extracted using DAPM model and the ridge contour details are taken by applying Mexican hat wavelet transform.

In order to extract the level 3 features the 1000 dpi images of 40 subjects are taken and tested. From the results obtained it is clear that higher recognition rate can be achieved by including level 3 features than the results of matching process using just two levels of features. The results obtained in matching by using level 3 features is then compared with the results found by using minutiae features and it's clear that level 3 features remarkably reduces the False Rejection Rate.

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Table1: Test cases for fingerprint recognition system

Test cases	No of training Images (per subject)	No of tested Images (per subject)
Case 1	4	4
Case 2	2	6

Table 2: Results of Orientation matching for test case 1

No. of Subjects	No. of Training Images	No. of Testing Images	No. of Images Accepted	No. of Images Rejected
10	40	40	38	2
20	80	80	78	2
30	120	120	117	3
40	160	160	156	4

Table 3: Results of Orientation matching for test case 2

No. of Subjects	No. of Training Images	No. of Testing Images	No. of Images Accepted	No. of Images Rejected
10	20	60	57	3
20	40	120	115	5
30	60	180	172	8
40	80	240	231	9

Table 4: Results of Minutiae matching for test case1

No. of Subjects	No. of Testing Images	No. of images accepted in level1 matching	No. of images accepted in level2 matching	No. of images rejected in level2 matching	GAR
10	40	38	31	7	77.5
20	80	78	64	14	80
30	120	117	99	18	82.5
40	160	156	136	20	85

Table 5: Results of Minutiae matching for test case2

No. of Subjects	No. of Testing Images	No. of images accepted in level1 matching	No. of images accepted in level2 matching	No. of images rejected in level2 matching	GAR
10	60	57	47	10	78.3
20	120	115	94	21	78.3
30	180	172	142	30	78.8
40	240	231	199	32	82.91

Table 6: Results of level3 matching for test case 1

No. of Subjects	No. of Testing Images	No. of images accepted in level1 matching	No. of images accepted in level2 matching	No. of images rejected in level2 matching	No. of images accepted in level3 matching	No. of images rejected in level3 matching	GAR
10	40	38	31	7	6	1	92.5
20	80	78	64	14	11	3	93.75
30	120	117	99	18	14	4	94.16
40	160	156	136	20	16	4	95

Table 7: Results of level3 matching for test case 2

No. of Subjects	No. of Testing Images	No. of images accepted in level1 matching	No. of images accepted in level2 matching	No. of images rejected in level2 matching	No. of images accepted in level3 matching	No. of images rejected in level2/level3 matching	GAR
10	60	57	47	10	7	3	90
20	120	115	94	21	13	8	89.16
30	180	172	142	30	17	13	88.33
40	240	231	199	32	18	14	90.41