A Novel Image Alignment and a Fast Efficient Localized Euclidean Distance Minutia Matching Algorithm for Fingerprint Recognition System

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Abstract: *A fingerprint recognition system involves several steps. In such recognition systems, the matching of unequal number of minutia features is the most important and challenging step in fingerprint based bio-metrics recognition systems. In this paper, we used clustering based fingerprint image rotation algorithm, to improve the performance of the fingerprint recognition system and proposed a Localized Euclidean Distance Minutia Matching (LEDMM) algorithm for matching, which will give better results while comparing minutia sets of different sizes as well as in slightly different orientation during the matching process. The experimental results on the fingerprint image database demonstrate that the proposed methods can achieve much better minutia detection as well as better matching with improved performance in terms of accuracy.*

Keywords: *Clustering, LEDMM, euclidean distance, fingerprint image enhancement, fingerprint minutia detection, alignment, fingerprint matching.*

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1. Introduction

Fingerprint recognition is part of the larger field of biometrics. Other techniques of biometrics include face recognition, voice recognition, hand geometry, retinal scan, ear surface, etc.

1.1. Fingerprint Image and Minutia

A fingerprint is the feature pattern of one finger. It is believed with strong evidences that each fingerprint is unique. A fingerprint is composed of many ridges and furrows. Although, there are several fingerprint matching paradigms, we focus on minutia (ridge ending and ridge bifurcation) based approach which is known to be the most popular and accurate method for the verification. A ridge ending is defined as the point where the ridge ends abruptly and the ridge bifurcation is the point where the ridge splits into two or more branches as shown in Figure 1.

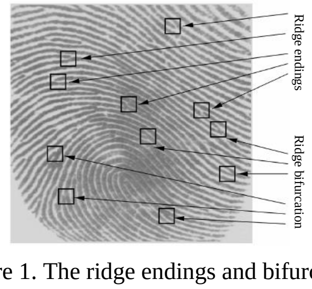

Figure 1. The ridge endings and bifurcation.

A fingerprint expert is often able to correctly identify the minutia by using various visual clues such as local ridge orientation, ridge continuity, ridge tendency, etc., as long as the ridge and furrow structures are not corrupted completely [4].

Figure 2 shows the clear view of a minutia. Minutia is characterized by its location and orientation.

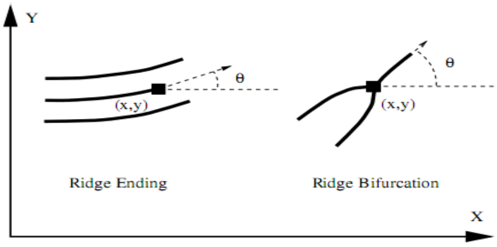

Figure 2. The characteristic attributes of a minutia.

1.2. Importance of Fingerprint Image Alignment Algorithm

Fingerprint image alignment algorithm is the most important step in any fingerprint based recognition systems since the results of minutia extraction algorithms and the minutia matching algorithms are very much depend on the clarity and orientation of the fingerprint image. In this work, we used clustering based fingerprint image rotation algorithm [6, 7] to improve the performance of the fingerprint recognition system. So, in addition to the fingerprint alignment algorithm, a better matching algorithm will lead to more accurate results. As shown in Figure 3, to implement a minutia extractor, a three-stage approach is widely used by researchers. They are preprocessing minutia extraction and post processing stage.

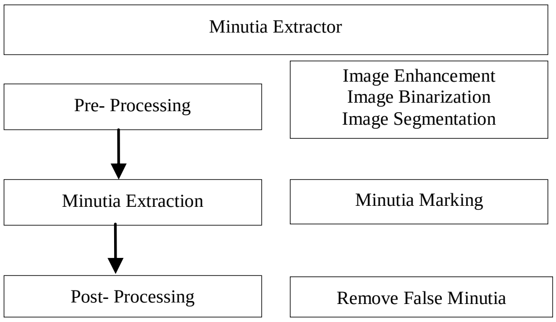

Figure 3. Three stage approach of minutia extraction.

1.3. Fingerprint Image Enhancement

The fingerprint enhancement techniques proposed by Ratha *et al*. [15] is based on the convolution of the image with Gabor filters, which has the local ridge orientation and ridge frequency. The algorithm includes normalization, ridge orientation estimation, ridge frequency estimation and filtering. Gabor filters are band pass filters that have both frequency selective and orientation selective properties [10] thus, the ridges are enhanced. Gabor filters [18] have both frequency selective and orientation selective properties, and have optimal joint resolution in both spatial and frequency domains. Therefore, it is appropriate to use Gabor filters as band-pass filters to remove the noise and preserve true ridge/valley structures The Gabor filter increases the contrast and reduces the noise.

$$G(x, y; \theta, f) = exp\left\{-\frac{1}{2}\left[\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right]\right\}cos(2\pi f x_\theta)$$
$$x_\theta = xcos\theta + ysin\theta \qquad (1)$$
$$y_\theta = -csin\theta + ycos\theta$$

In Equation 1, θ is the local orientation, f is the frequency, σ_x and σ_y are the standard deviation of the Gaussian envelope. In our previous work [14] the orientation of the fingerprint image also, has much influence on fingerprint image enhancement phase which increases the contrast and reduces the noise of the image. This leads to better minutia detection and minutia matching phase of the system.

1.4. Fingerprint Image Binarization

Image binarization is a process which transforms the 8bit gray image to a 1bit image with 0 value for ridges and 1 value for valleys. After the operation, ridges in the fingerprint are highlighted with black colour while valleys are white. Binarization is done to increase the contrast between the ridges and the valleys and hence, facilitates the extraction of minutia.

1.5. Fingerprint Image Segmentation

After image binarization the next step is fingerprint image segmentation. In general, only a Region Of Interest (ROI) is useful to be recognized for each fingerprint image. The image area without effective ridges and valleys is first discarded since it only holds background information. Then, the bound of the remaining effective area is sketched out since the minutia in the bound region is confusing with those spurious minutia's that are generated when the ridges are out of the sensor. To extract the region of interest, two steps are followed: Block direction estimation and ROI extraction by morphological methods.

1.6. Fingerprint Image Ridge Thinning

Now, the enhanced and segmented image needs to be thinned before the minutia can be extracted from the image. Thinning is a morphological operation that erodes the ridge pixels until they are one pixel wide.

1.7. Fingerprint Image Minutia Detection

The binary image is thinned as a result of which a ridge is only one pixel wide. The minutia points are thus those which have a pixel value of one (ridge ending) as their neighbour or more than two ones (ridge bifurcations) in their neighbourhood. In our work, the post processing is not required; because the fingerprint image alignment algorithm and proposed Localized Euclidean Distance Minutia Matching (LEDMM) algorithm will reduce the false minutia points.

1.8. Other Fingerprint Matching Techniques

To implement a minutia matching, different approaches were used by different researchers. In general, minutia matcher chooses any two minutias as a reference minutia pair and then matches their associated ridges first. If the ridges match well [2] two fingerprint images are aligned and matching is conducted for all remaining minutia. The large number of approaches to fingerprint matching can be coarsely classified as correlation-based matching, minutia-based matching and pattern-based (or image-based) matching. We have implemented minutia based matching technique using LEDMM algorithm.

1.9. Related Works on Image Registration or Alignment

Registration or alignment is a process through which the correct transformation is determined. The registration based method called 'Automatic Image Registration' by Artyushkova [1] has developed an image registration or alignment algorithm, which works good with an assumption that distortion of the image is not very large and images must have correct relative sizes with respect to each other (no resizing is incorporated in this registration). In this method, mutual information is calculated using joint histogram calculation between two images. Another fingerprint registration method is by maximization of mutual information; it uses mutual information as the similarity measure and aligns images by maximizing mutual information between them under different transformations [11]. Mutual information describes the uncertainty in estimating the orientation field at a certain location given another orientation field. The more similar or correlated the orientation fields are, the more mutual information they have. Mutual information measures the statistical dependency between two random variables. The physical meaning of Mutual information is the reductions in entropy of Y given X. Viola *et al.* [19] have proposed that registration could be achieved by maximization of mutual information. This algorithm uses mutual information between template and input's direction features to align the fingerprints.

1.10. Related Works on Minutia Matching

Many researchers have proposed matching algorithms to decide whether two fingerprints were obtained from the same finger. Ratha *et al.* [16] have presented an alignment algorithm using Hough transform and a matching algorithm utilizing matching box. Wahab *et al.* [20] showed an alignment and a matching algorithm that used the similarity of local structures composed of neighbor minutia. Jain *et al.* [8] have exhibited an improved matching algorithm which used a dynamic programming to adjust the size of matching box. Luo *et al.* [12] have proposed a matching algorithm which changed the size of matching box according to the distance from reference minutia. Jiang and Yau [9] have amended the matching algorithm proposed by Wahab *et al.* [20]. Bhowmik *et al.* [3] have derived a minutia matching algorithm using the smallest minimum sum of closest euclidean distance. Tan and Bhanu [17] proposed a traditional genetic-algorithm based method fingerprint matching method. In this method, a genetic algorithm with traditional roulette wheel selection, uniform crossover and binary flip mutation was used for fingerprint matching. Jaam *et al.* [5] have proposed fingerprint verification system for minutia matching and verification based on genetic algorithm. Qader *et al.* [13] have proposed fingerprint matching using Zernike moments invariant approach.

The rest of the paper is organized as follows: Section 2 deals with k-means clustering based fingerprint image alignment algorithm. Section 3 deals with the existing Euclidean distance matching and the proposed LEDMM algorithms. Sections 4 gives the implementation details and the conclusions are given in section 5.

2. The Fingerprint Image Alignment Algorithm using K-Means Clustering

Let us assume the pixels of the two dimensional fingerprint image plotted as three data points of x, y and gray level.

1. The fingerprint image pixels are assumed as data points in 2D space as shown in Figure 4.

Figure 4. Data points in 2D space.

2. The data points were clustered in to two groups using k-means clustering algorithm. The green line showing the cluster boundary as shown in Figure 5.
3. The points C1 and C2 are the centers of the two clusters.

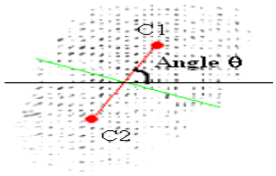

Figure 5. Cluster points C1 and C2 with cluster boundary shown in green line.

4. A line connecting C1 and C2 will be almost equal to the inclination of the fingerprint image.
5. The inclination angle θ can be measured from the base of the image.

$$\theta = atan\ ((x1\text{-}x2)/(y1\text{-}y2)) \quad (in\ radians)$$
$$\theta = \theta * (180/pi) \quad (in\ degree)$$
$$if\ \ \theta < 0$$
$$\theta = 90 + \theta$$
$$else$$
$$\theta = -(90 - \theta)$$
$$end$$

6. Now, rotating the image by angle θ as shown in Figure 6.
7. The direction of rotation can be decided with respect to the location of the point C1 in the top two quadrants of the four quadrants.

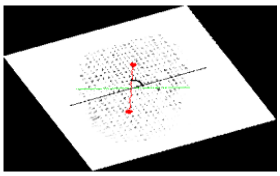

Figure 6. Rotated image in 2D space.

8. This will finally give the well aligned image as shown in Figure 7.

Figure 7. Fingerprint image after alignment.

3. The Matching Algorithms

3.1. Algorithm 1: The Normal Euclidean Distance based Minutia Matching Algorithm

Let *S* be the set of minutia feature of size *m* which is to be matched with the target minutia features set *T* of size *n*. The sets *S* and *T*, which we are matching, should be same kind of feature that may be the attributes of ridge endings or ridge bifurcation.

Algorithm 1 for normal way of matching two unequal feature sets will be as follows:

Algorithm 1: Normal euclidean distance based minutia matching algorithm.

S = {*s*1, *s*2, *s*3, ..., *sm*}
T = {*t*1, *t*2, *t*3, …,*tn*}
Let D be the distance matrix of size m x n
for i=1 *to m*
for j=1 *to n*
  $D(i, j)=EuclideanDistance(s_i, t_j)$
 End
End
Dist=*mean*(*D*)

3.2. Algorithm 2: The Proposed LEDMM Algorithm

There may be lot of false minutia points in source as well as target image. In the normal Euclidean match algorithm all the minutia points in the source and target images were used in the matching process. This will lead to inaccurate result due to some of the false minutia points in the source as well as target image. The proposed Algorithm 2 minimizes this error by only considering the distances of a set of nearer points (within a small distance *d* as shown in Figure 8, the circles are having radius *d*) in the target image for each points in the source image.

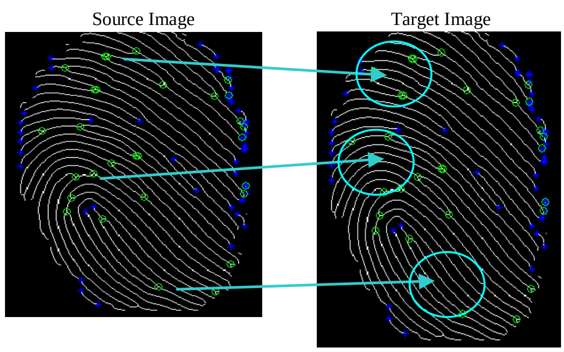

Figure 8. Fingerprint source and target image matched with a small radius (d=10 pixel radius).

Algorithm 2: Proposed LEDMM algorithm**.**

S= {*s*1, *s*2, *s*3, …, *sm*}
T= {*t*1, *t*2, *t*3, …. *tn*}
if (*m*>*n*)
A=*S*
B=*T*
else
 A=*T*
 B=*S*
end
Let PA be the number of elements in A, PB be the number of elements in B
for i=1 *to PA*
 Let D be the matrix of size (*PA X* 1)
for j=1 *to PB*
 D(*j*)= *Euclidean*(*A*(*i*), *B*(*j*))
end
Let I be the set of index values of elements of D which are less than a small distance d
Find N, the set of elements of D that belongs to the points nearer to A(*i*) *as follows*
N=*D*(*I*)
Let PC be the number of elements in N
if (*PC*> 0)
 AvgDist=*mean*(*N*)
else
 AvgDist=*d*
end
D(*i*)=*AvgDist*
end
Dist= *mean*(*D*)

In our implementation we used d as 10 pixel radius.

4. Implementation Results and Analysis

Figure 9 shows the evaluation strategy used in this work.

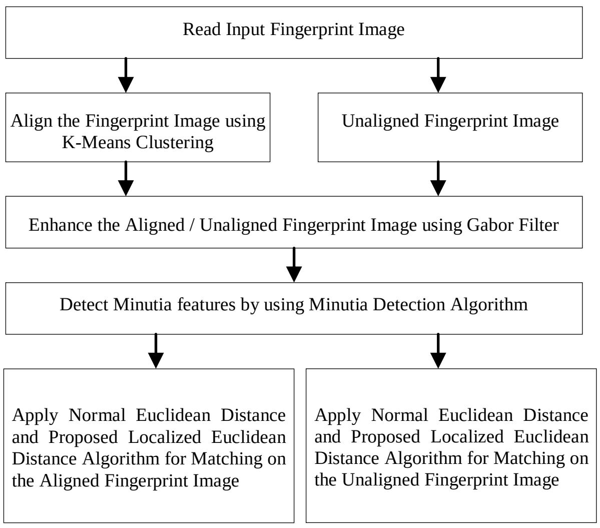

Figure 9. The evaluation model.

4.1. Fingerprint Database Used For Evaluation

A fingerprint database from the Fingerprint Verification Competition 2000 (FVC2000) and FVC2002 are used to test the experiment performance. FVC2000 was the first international competition for fingerprint verification algorithms. This initiative is organized by Maio D., Maltoni D., Cappelli R. from Biometric Systems Lab (University of Bologna), Wayman J.L from the U.S. National Biometric Test Center (San Jose State University) and Jain *et al.* [8] from the pattern recognition and image processing Laboratory of Michigan State University. In FVC2000, four different “sensors” were used to cover the recent advances in fingerprint sensing techniques. In fact, databases 1 and 2 were collected by using two small-size and low-cost sensors (optical and capacitive, respectively). Database 3 was collected by using a higher quality (large area) optical sensor. Sets of few selected images from the above database were used to evaluate the performance of the algorithms.

4.2. Sample Set of Results

Figure 10 shows some of the inputs as well as the corresponding outputs. In the second column images, the angle of rotation estimated by the K-Means based algorithm also, provided.

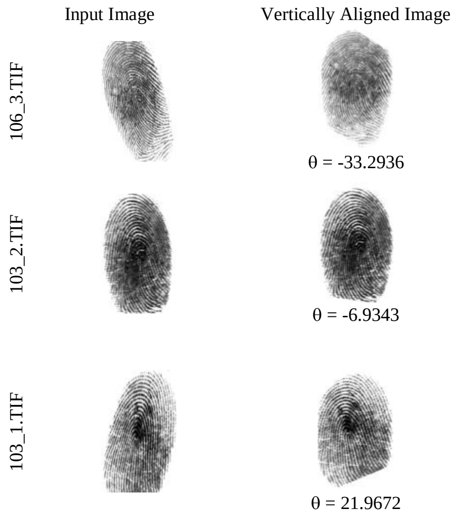

Figure 10. Results of rotation

4.3. The Results of Matching Algorithms

The better minutia is detected only after fingerprint image alignment, also reduces the false positives. Hence, if we use the aligned fingerprint image for the detection of minutia and minutia matching, then we may expect better accuracy in recognition [3]. The Table 1 shows the differences in performance of normal and proposed LEDMM algorithm. If we see Table 1, it is obvious that the performance of proposed matching algorithm was ideal in all tests. After sorting all the distances in ascending order, the proposed LEDMM algorithm can able to find the correct matching image in the first position of the top three matching images. The last row of Table 1 shows the average minimum distance of the matching image in normal and proposed method.

The Equal Error Rate (EER) is commonly used to summarize the accuracy performance of a matching system is defined as EER where the False Acceptance Rate (FAR) is equal to False Rejection Rate (FRR).

$$TSR\ (total\ success\ rate) = (100\text{-}EER) \tag{2}$$

A comparative analysis is done using the FVC2002 databases four datasets DB1, DB2, DB3 and DB4. The proposed method LEDMM is compared with Tan and Bhanu [17] method. In Table 2, [17] method needs 7.9 seconds for matching on DB1, whereas the proposed method need only 3.3 seconds. This shows that the proposed algorithm is faster than [17] method. The TSR values of the proposed method are 98.8%, 98.4%, 98.1% and 98.2% respectively.

Table 1. The normal and proposed matching algorithm results with and without alignment.

Input Image	Results without Alignment				Results with Alignment			
	Normal Matching Algorithm		Proposed LEDMM Algorithm		Normal Matching Algorithm		Proposed LEDMM Algorithm	
	Location of the Correct image in the Top 3 Match	Distance of top most Matching Image	Location of the Correct image in the Top 3 Match	Distance of top most Matching Image	Location of the Correct image in the Top 3 Match	Distance of top most Matching Image	Location of the Correct image in the Top 3 Match	Distance of top most Matching Image
101_1.TIF	None	199.98	1	8.10	2	212.23	1	7.88
101_2.TIF	1	183.58	1	6.03	2	210.75	1	7.18
101_3.TIF	1	195.12	1	6.99	1	196.62	1	5.08
101_4.TIF	3	193.60	1	6.18	None	214.48	1	8.14
101_5.TIF	1	169.89	1	7.38	1	196.88	1	7.47
101_6.TIF	2	196.68	1	7.52	1	199.31	1	7.89
101_7.TIF	2	202.48	1	5.99	None	222.47	1	8.14
101_8.TIF	2	199.91	1	7.10	None	223.72	1	4.80
102_1.TIF	2	192.72	1	5.58	None	224.60	1	6.77
102_2.TIF	None	208.37	1	6.32	None	230.01	1	6.64
102_3.TIF	3	201.38	1	8.19	3	215.95	1	7.65
102_4.TIF	None	209.00	1	6.92	None	218.99	1	7.53
102_5.TIF	None	204.76	1	7.05	2	235.26	1	7.53
102_6.TIF	1	196.10	1	6.23	3	227.31	1	7.85
102_7.TIF	1	176.30	1	6.91	2	205.14	1	7.85
102_8.TIF	None	201.75	1	5.44	None	221.54	1	7.91
103_1.TIF	None	219.09	1	6.94	None	235.38	1	6.72
103_2.TIF	1	196.00	1	5.12	1	211.39	1	5.70
103_3.TIF	None	229.45	1	7.24	None	241.75	1	4.72
103_4.TIF	1	202.89	1	5.94	None	235.43	1	7.42
103_5.TIF	None	223.46	1	7.02	None	223.66	1	7.07
103_6.TIF	None	213.72	1	6.40	None	244.53	1	7.55
103_7.TIF	1	184.09	1	4.72	None	226.72	1	4.86
103_8.TIF	None	219.41	1	5.93	None	251.50	1	7.21
104_1.TIF	None	211.70	1	2.16	3	231.78	1	3.57
104_2.TIF	2	205.41	1	4.04	None	252.14	1	4.40
104_3.TIF	1	195.48	1	4.34	None	240.57	1	5.50
104_4.TIF	3	214.86	1	4.85	None	257.15	1	4.90
104_5.TIF	1	187.49	1	3.52	1	187.57	1	3.63
104_6.TIF	2	193.71	1	2.01	None	234.72	1	4.17
104_7.TIF	3	201.74	1	5.58	None	245.65	1	7.38
104_8.TIF	None	209.38	1	4.04	None	231.79	1	4.73
Avg. Dist.		201.23		5.87		225.18		6.44

Table 2. TSR, EER and average matching times of the four data sets of two different methods.

FVC 2002 Database	Tan *et al.* [18] method			Proposed LEDMM		
	EER%	TSR%	Average Matching Time(s)	EER%	TSR%	Average Matching Time(s)
DB1	1.5	98.5	7.9	1.2	98.8	3.3
DB2	2.1	97.9	8.1	1.6	98.4	4.3
DB3	4.2	95.8	8.5	1.9	98.1	5.3
DB4	3.4	96.6	8.0	1.8	98.2	4.3

The results reveal an interesting tradeoff between the matching accuracy and efficiency. Findings:

1. The proposed finger print image alignment algorithm enhanced the overall accuracy.
2. The proposed matching algorithm significantly enhanced the accuracy.

In our repeated tests, we observed the following:

1. Without the proposed alignment and matching algorithm the accuracy was in between 80 to 90%.
2. After the proposed alignment, the accuracy was improved around 95%.

With the use of proposed alignment and matching algorithm, the accuracy was very much improved and it became greater than 95% and was around 100% for a small data set.

5. Conclusions and Future Work

The proposed LEDMM algorithm has successfully implemented using Matlab 6.5 and the results were compared with normal Euclidean distance based method. Arrived results were found to be more significant and promising. The performance of the proposed image alignment and minutia matching algorithms in terms of matching accuracy is improved very much. There was 10% improvement observed during our repeated trials with different sets of images, the observed accuracy was around 95% and it was almost 100% if the data set is small.

Future works may evaluate the difference in recognition with and without the proposed fingerprint image alignment phase and address the performance of the proposed matching algorithm with very large data set.

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