INSTITUTE OF DEVELOPMENT AND RESEARCH IN BANKING TECHNOLOGY

SUMMER RESEARCH INTERNSHIP

Fingerprint Indexing using Extended Set Triangulation.

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July 4, 2014

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ACKNOWLEDGEMENT

I express my deep sense of gratitude to my Guide Dr.M.V.N.K Prasad, Associate Professor, IDRBT for giving me an opportunity to do this project in the Institute for development and research in Banking Technology and providing all the support and guidance needed which made me complete the project on time.

I am also thankful to Indian Academy of Sciences, for giving me this golden opportunity to work in a high-end research institute like IDRBT.

I also thank my parent institute Dhirubhai Ambani Institute of Information and Communication Technology, Gandhinagar for allowing me in doing internship with IDRBT.

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1 INTRODUCTION

With the increasing need of security systems for personal authentication, the use of biometrics has gained importance in recent times. Biometric Recognition is the use of physiological (fingerprint, faces, iris, palm etc) and behavioral (gait, voice, etc) characteristics for recognizing the identity of individual. Biometric Recognition is of two types, verification and Identification. Verification refers to the process in which a person verifies his identity with the identity of the person whom he claims to be i.e., it is one to one match, whereas in Identification the system must determine the identity of the person by searching all templates in the database. Identification refers to an one to N match in the database. To put in simpler words, verification answers the question "*Am I Whom I claim I am?*" and Identification answers the question "*Who am I?*". In either of the cases, the goal of recognition is to quickly determine if an object or template is in the database and to retrieve those objects or templates which are most similar with the unknown object or query template[26]. Accuracy and Efficiency are the defining factors for any Biometric recognition system because everything in the end boils down to how much we are using and how fast we are producing results.

Fingerprint recognition is one of the most widely accepted biometric technique because of its uniqueness, immutability, ease of extraction and its numerous availability (ten fingers) and are extensively used in forensic and civilian applications[Source : www.biometrics.gov].

A naive approach for fingerprint identification would be to compare the given template with all the templates in the database. However, with modern databases, which contain millions of templates, the required processing would have a very large response time and a very low performance which is not acceptable in most of the real time systems. To overcome these difficulties, several researchers have proposed different methods to narrow down the search space.These approaches can be broadly categorized into two types, Classification and Indexing. The goal of these approaches is to reduce the potential candidates that have to be matched with the query image when performing matching. Because fingerprint matching algorithms are generally computationally very expensive, the candidate list produced by the these approaches should be as small as possible with high probability of containing the templates that are most similar the query image. These type of approaches can be considered to be a front end recognition systems which is to be followed by a backend verification system.

1.1 CLASSIFICATION

Classification based approaches split the databased into fixed number of classes. During Identification , first the class of the template is determined and the matching is done only with the fingerprints of the same class. Henry [3] has classified fingerprint images into 5 major classes, plain arch, tented arch, left-loop, right-loop and whorl based on the patterns formed by ridges. Jain[8] has used a novel representation (FingerCode) and a two stage classifier to classify the images into five classes.Classification based approaches can be broadly classified into five categories[4]: syntactic-based [5,6], structural-based[7], statistical-based[25], rule-based and neural network-based[24] methods.

Figure 1.1: Fingerprint classification based on (a) Left Loop(b) Right Loop(c)Arch(d)Tented Arch (e) Whorl.

This type of approaches have a serious disadvantage mainly because the number of classes into which fingerprints can be divided is small and it is fixed.Also the distribution of fingeprints among these classes is also very uneven because of small interclass variations. Fingerprint classification in most of the cases does not account for translations or rotations and noises of fingerprint images. This led the researchers build systems that are not based on classification but represent each fingerprint template in a very stable robust and effective manner so that in the identification phase , the number of candidates to be selected is reduced.

1.2 Indexing

Any indexing based approach can be divided into two phases: Preprocessing (building the database by enrolling the templates) and fingerprint verification. During preprocessing features that are robust, that are abundantly available in the template and that uniquely represent a fingerprint are used to form indices. These indexed locations are filled with entries containing reference to the template. During the verification step, the same features are extracted from the query templates and are used to from the indices. The references to the templates that are present in the indexed entries are retrieved and the similarity between the templates is computed and finally a potential list of candidates called the candidate list is produced.

There are several minutia based approaches reported in the literature over the past decade. Triangulations of minutia is one area that has gained a lot of interest in researchers. Most of the minutia based methods derive the robust features from the triplets of minutia and use hashing techniques to perform indexing. R.S. Germain et al.[27] used the triplets of minutiae in their indexing procedure. Bhanu [14] has used all possible triangles along with triangle invariant features such as angles, handedness, type and direction for indexing. Using all possible triangles, a large number of hypothetical matches ($O(N^3)$) are generated making the indexing approach ineffective.Bebis[23] had used Delaunay triangulation instead of using all possible triplets.

Although compared to all possible triangles, delaunay triangulation reduces the computation cost drastically, they are not very stable under distortions. Even for small distortions there can be change in the entire structure of triangulation. Hence various efforts we made by researchers to overcome this drawback. Xiang[15] has used Lower Order Delaunay triangulations(order 0 and order 1) to perform indexing. The features used for indexing were the minutia detail and the attributes of the lower order Delaunay triangles such as its handedness, angles, maximum edge and relative angles between orientation field and its edges. Andres [20] has used extended set which has been derived from Delaunay triangulation to perform indexing. They have used minutia coordinates, triangle sign, ridge count and relative angles between orientation field and edges to perform indexing. Extended set is very tolerant to missing and spurious minutia which is one of major factor causing distortions in fingerprint indexing. We have used extended set for creating triangulation in our approach.

Global and local ridge features were also used to perform indexing. Umarani [21] has used core point, which is a global feature in the fingerprint along with Minutia Binary Vector, which represents the local neighborhood of the minutia for fingerprint indexing. Their technique encodes spatial and directional relationship between core point and each minutia to build a two dimensional hash table. Jiang [22] proposed an approach which uses orientation field and dominant ridge distances as the features for hashing into the database.

Level three features such as pores and ridge counters were used by Anil[16] for performing high resolution fingerprint matching. Hoi et al[17] has made an effort by using code word for each feature point. Some the other approaches use transform based algorithms such as SIFT [18] and Finger code [8] [19] for indexing into the database.

To make fingerprint indexing, robust distortions between different fingerprints of same person should be accounted for. In our approach, we use Extended Set Triangulation which has been derived from Delaunay triangulation. We classify these triangles into 8 classes based on the type of the minutia and use the minutia directions and triangle lengths as the parameters to perform indexing.

The rest of the document is organized as follows: Section 2, some of the basic concepts, which are useful for understanding the document is presented. Section 3, the proposed approach is expalained. In Section 4, the experimental results of the algorithm are shown.

2 Background

Fingerprints are the impressions produced by the friction ridges on the human finger. Minutia which represent the singularities present on the fingerprint are of two types bifurcations and endings. Bifurcation is a point where a ridge splits into two ridges while an ending is an end point of the ridge. In our approach we use these two types of minutia to classify the triangles.

Triangulation: Let P = $\{p_1,....,p_n\}$ be a point set. A triangulation of P is a maximal planar subdivision whose vertex set is P. A maximal planar subdivision is a subdivision S such that no edge connecting two vertices can be added to S without destroying its planarity.

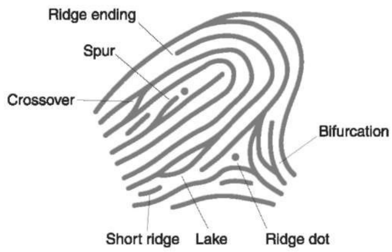


Figure 2.1: Types of Minutia

2.1 Delaunay Triangulation

Delaunay Triangulations: Let P = {p_1, p_2,....,p_n } be a set of points in the plane. A triangulation P is said to be a Delaunay Triangulation if and only if for every triangle in T, it satisfies a property that its circumcircle contains no other point of P.
A Delaunay graph is represented by G = {P,E} where P is the points in the Delaunay graph and E are the edges in its Delaunay triangulation.

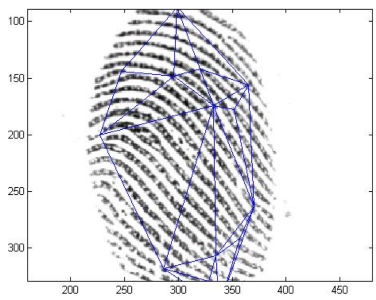
Properties of Delaunay Triangulations:

1. Insertion of Spurious minutia in the fingerprint template only effects the triangles whose circumcircle contain that point. Hence, it effects only the local structure keeping the global structure intact.

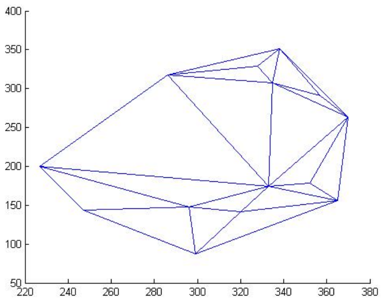
2. The Delaunay Triangulation of a set of points is unique if there is no circumcircle with more than three points on its border.

3. The Delaunay triangulation maximizes the minimum angle. Compared to any other triangulation of the points, the smallest angle in the Delaunay triangulation is at least as large as the smallest angle in any other.

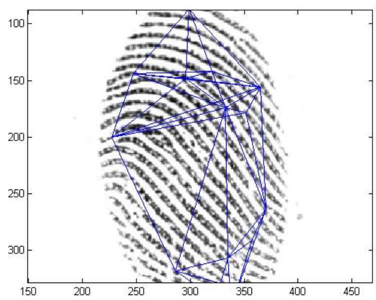
4. The union of all triangles of a Delaunay triangulation of a set of points P forms the convex hull of P. The Delaunay triangulation of a set of points P has 2N-2-kriangles and 3N-3-kedges, where N is the number of points in P and k is the number of points of P forming the convex hull.



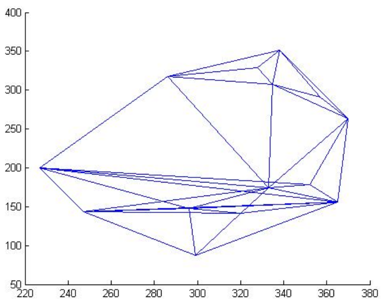
(a) Delaunay Triangulation with Image



(b) Delaunay Triangulation



(c) Extended Set with Image



(d) Extended Set

Figure 2.2: Delaunay Triangulation Vs Extended Set for a fingerprint

2.2 EXTENDED SET

Let P ={p_1,p_2,....,p_N} be a set of points in the plane, where G={P, E},is its Delaunay graph and T is its Delaunay triangulation.To be able to formally define the expanded triangle set ofP, we first define thetriangular hull of any point $p_i \in$ P.

Triangular hull: Let p_i be a point of P. The set N_i ={p_j | {p_j,p_i} ∈ E} denoted the point set formed by all the adjacent vertices of p_i in the Delaunay graphG. The triangular hull of p_i is defined as the Delaunay triangulation of the planar point set N_i, and it is denoted by H_i. As we can see, the number of points in each set N_i is the degree of p_i in the graph G, and it is denoted by d_i.

Expanded triangle set : The expanded triangle set of P is defined as R = {$H_1 \cup H_2 \cup H_3 \cup H_4 \cup .... \cup H_N$. The set R includes the triangles in the Delaunay triangulation of P and any triangle in the triangular hulls of the points in P. Therefore,|R|≥|T|. The number of triangles in R is lesser than 13N-25, where N is the number of minutua points[20].

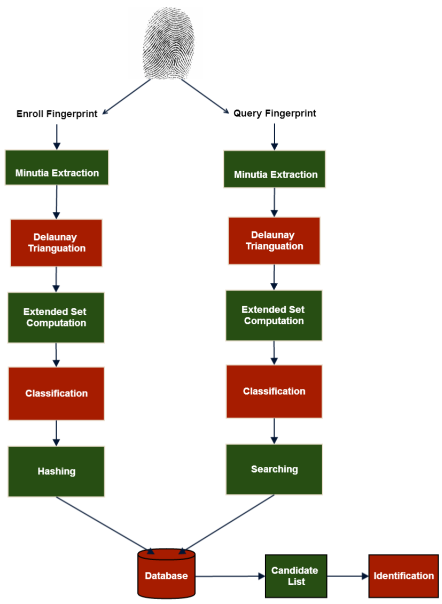


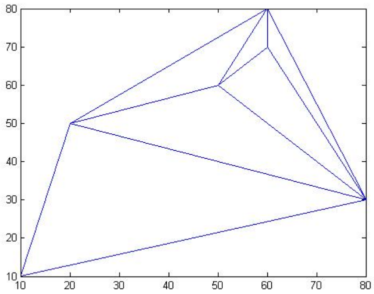
Figure 3.1: Types of Minutia

3 Proposed Aprroach

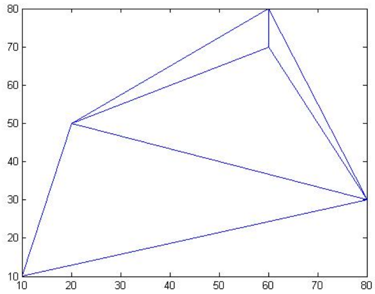
3.1 Preprocessing stage

Feature selectivity is one of the most important steps of any indexing approach. Features with lower discrimination power tend to give very similar indices which further increases the searching time and reduces the efficiency of the approach [11].

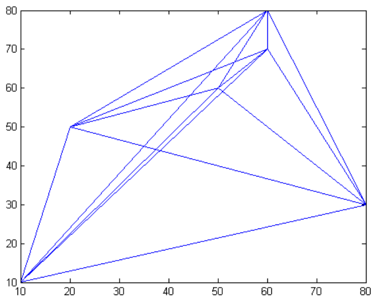
Using Extended set execution times of the algorithm are similar to Delaunay Triangulation since both of them produce O(N) triangles.The advantage Extended set has is that it contains all Delaunay Triangles that are formed when each minutia is removed individually[20]. Because most of the minutia features change under elastic distortion, it is very essential to choose features that are invariant to distortion for indexing. Even if the distortion is applied to the fingerprint image, the neighborhood structure of minutia and its shape remains intact. Extended set triangulations store the local structure of the minutia, hence using such a method under distortions would produce better results.Fig(2.2) shows Delaunay triangulation and Extended set for a fignerprint. Extended Set contains all Delaunay Triangles that are formed when each minutia is eliminated individually. This property ensures that in cases of missing or spurious minutia, some matching are definitely found between the distorted and the original image. Fig(3.2-a) and Fig(3.2-c) shows the Delaunay triangulation and expanded set for a set of points. Fig(3.2-b) and Fig(3.2-d) show the Delaunay triangulation and expanded set of the same set of points with center minutia removed. We can see the correspondence of triangles in Fig (3.2-a) and Fig (3.2-b) with the Fig(3.2-c). Also, it can be concluded from Fig(3.2) that the correspondence between the triangles in the extended set (Fig 3.2-c and Fig 3.2-d) is more than that between the triangles in the Delaunay triangulation (Fig 3.2-a and Fig 3.2-b).



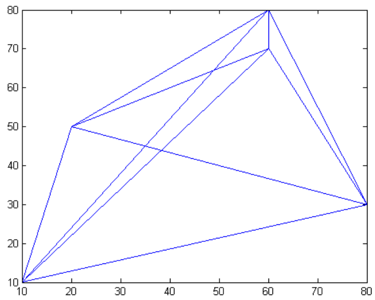
(a) Delaunay Triangulation



(b) Delaunay Triangulation with the center minutia removed



(c) Extended Set



(d) Extended Set with the center minutia removed

Figure 3.2: Delaunay Triangulation Vs Extended Set for a fingerprint

The proposed approach represents fingerprints in terms of their minutia. Each minutia can be represented uniquely by using its co-ordinates m(x, y). Let the graph S{P, E} denote the extended set triangulation for these minutia, where P represents co-ordinates of the minutia points and E represents the edges between them in the triangulation.Fig(3.3) represents a mintuia triplet with vertices V1,V2 and V3.

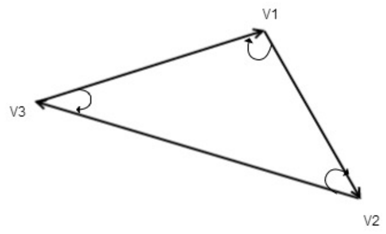


Figure 3.3: A Minutia Triplet

Let t be any triangle in S and let it be represented by minutia triplet m^1 = {x1, y1} m^2 = {x2, y2} m^3 = {x3, y3} which are sorted in increasing order according to the length of the opposite side.

If a minutia m is an endpoint we represent its type m_t = 0 and if it is a bifurcation, it is represented by a 1 i.e m_t = 1.

The triangle class t_c is defined by the binary integer $m_t^1 m_t^2 m_t^3$ i.e., if m^1 is an end point (m_t^1=0), m^2 an bifurcation (m_t^2 = 1) and m^3 an end point (m_t^3=0), then the triangle class t_c is denoted by 010 i.e 2. From the above definition of triangle class, the number of classes into which triangle can be divided is 8 starting form 0 where all minutia are end points to 7 where all minutia are bifurcation points. The above definition of triangle class is invariant to elastic distortion and rotation. Table(3.1) represents the classification of delauanay triplets into 8 categories.

Let m_θ^i be the orientation of the minutia point with respect to x axis. Let the sides of the triangles be represented by m^1m^2, m^2m^3, m^3m^1. The angles that m_θ^1 makes with m^1m^2 is denoted by θ_1 and the angle that m_θ^2 makes with m^2m^3 is denoted by θ_2. These features of triangle, θ_1 and θ_2 are also rotation and distortion invariant as in both the cases, although the angles changes but the relative change is always zero.

Let l_1,l_2,l_3 be the lengths of sides, m^1m^2,m^2m^3,m^3m^1 in the triangle t. These lengths have been stored along with the fingerprint ID into the image database. They have been used to reduce the number of potential matches that have to be made with the query fingerprint.
A 3D index X = (t_c,θ_1,θ_2) is formed for each triplet in the fingerprint image. We use the (t_c,θ_1,θ_2) of the triplet as an index into the 3D hash table A, of size 8x180x180. The fingerprint ID and the lengths of sides of triagnles have been stored as entries in the index inside the hash table.

$$A(t_c,\theta_1,\theta_2) = (f_i d, l_1, l_2, l_3)$$

where $f_i d$ represents the fingerprint identity to which the triplet belongs and l_1, l_2,l_3 are the lengths of sides of triangle.The same procedure is repeated for every triangle in S and the so obtained hash table is used for identification of authenticity of a user.

Table 3.1: Triplet Classification

Triplet Type	Vertex Minutia Type		
t_c	V1	V2	V3
0	e	e	e
1	e	e	b
2	e	b	e
3	e	b	b
4	b	e	e
5	b	e	b
6	b	b	e
7	b	b	b

3.2 The Verification Step

During verification, the features, t_s,θ_1,θ_2,l_1,l_2,l_3} are extracted for every triangle in the query fingerprint. The triplet $\{t_s,\theta_1,\theta_2\}$ is used for indexing into the hash table.

Let D represent the entry in the hash table corresponding to index $\{t_s, \theta_1, \theta_2\}$.

Now, for each quadruplet $q_i\{f_{ID}, l_1,l_2,l_3\}$ present in D, we find the similarity between the triangle represented by q1 and the triangle being considered.

Similarity between two triangles: Two triangles represented by (l_1^1, l_2^1, l_3^1) and (l_1^2, l_2^2, l_3^2) are said to be similar if and only if the maximum difference between the corresponding angles of the triangles lie within a certain threshold th i.e., th > max (l_1^1-l_1^2, l_2^1-l_2^2, l_3^1-l_3^2).

Now, we use a vote based strategy for accumulating the number of similar triangles for each database template with the query template. A vote is given to a template f_{ID} only if the triangle represented by f_{ID} and the triangle being considered are said to be similar.

Rather than considering the triangles exactly at the index $\{t_s, \theta_1, \theta_2\}$, we consider all the triangles that belong in the range $\{t_s,\theta_1 \pm h,\theta_2 \pm h\}$ to account for any distortions that might have present in the fingerprint templates.

4 Experimental Results

In this section we describe the experimental results of our proposal and we compare our results with some other state of art indexing approaches present today.

We have experimented our technique on some of the well known datasets:

- FVC2002 DB1: The first FVC 2002 dataset comprises of 800 finger print images from 100 fingers(8 impressions per finger). They have been captured using the optical sensor

"TouchView II" by Identix and each image is of 388x374 (142 Kpixels) at 500dpi.

- FVC2002 DB2: This dataset comprises of 800 images from 100 fingers (8 impressions per finger) that have been captured using the optical sensor "FX2000" by Biometrika and each image is of size 296x560 (162 Kpixels) at 569 dpi.
- FVC2002DB3: This dataset comprises of 800 images from 100 fingers (8 impressions per finger) that have been captured using the Capacitive sensor "100 SC" by Precise Biometrics and each image is of size 300x300 (88 Kpixels) at 500 dpi.
- FVC2002DB4: This dataset comprises of 800 images from 100 fingers (8 impressions per finger) that have been captured using the SFinGe v2.51 and each image is of size 288x384 (108 Kpixels) at about 500 dpi. These fingerprints have been synthetically generated.
- FVC2004 DB1: This dataset comprises of 800 finger print images from 100 fingers 8 impressions per finger). They have been captured using the optical sensor "V300" by CrossMatch and each image is of 640x480 (307 Kpixels) at 500dpi.
- FVC2002 DB2: This dataset comprises of 800 images from 100 fingers (8 impressions per finger) that have been captured using the optical sensor "U.are.U 4000" by Digital Persona and each image is of size 328x364 (119 Kpixels) at 500 dpi.
- FVC2002DB4: This dataset comprises of 800 images from 100 fingers (8 impressions per finger) that have been captured using the SFinGe v3.0 and each image is of size 288x384 (108 Kpixels) at about 500 dpi. These fingerprints have been synthetically generated.

We have extracted the minutia points of the fingerprint templates from the above databases using Neurotechnology Verifinger SDK. Verifinger has not enrolled 1 image from 2002 DB1, 1 image from 2002DB2, 19 images from 2002DB3, 14 images from 2002DB4 and 8 images from 2004DB4 because of low quality. We have decreased the quality threshold of the SDK for extraction to enroll the unenrolled fingers.

4.1 Evaluation of the indexing approach

The indexing approach was measured using two factors the penetration rate and hit rate.

Penetration rate: It denotes the average length of the candidate list retrieved for each probe. It is defined as

$$P_r = \frac{1}{Q}\sum_{i=1}^{Q}\frac{d_i}{N},$$

where d_i is the length of candidate list for i_{th} query image, N is the size of the database, Q is the number of query images used for experiment.

Hit Rate: It denotes the fraction of the probes for which candidate list contains the correct identity as the query probe. It is defined as

$$H_r = \frac{X}{Q} * 100\%,$$

where X is the number of probes for which correct identity has been retrieved and Q denotes the size of the number of queries made.

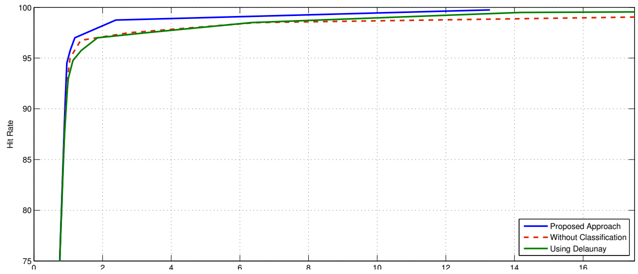


Figure 4.1: Hit Rate vs Penetration Rate Comparision for FVC-2002DB1

Fingerprint images are generally very noisy due to various factors such as fingerprint morphology and imaging conditions. Also, certain amount of noise is introduced by the minutiae extraction process. In order to account for variations in the fingerprint images of the same finger, it is often imperative to store in the database information from several different images of the same finger taken at different times. Although this increases memory requirements, it makes the system more robust to noise and distortions. To evaluate the accuracy of our proposal, in all the databases we have used 4 impressions out of 8 for creating the templates in the indexing table and the remaining impressions were used as the query probes.

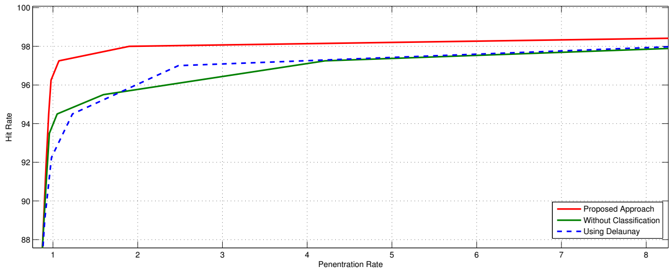


Figure 4.2: Hit Rate vs Penetration Rate Comparision for FVC-2002DB2

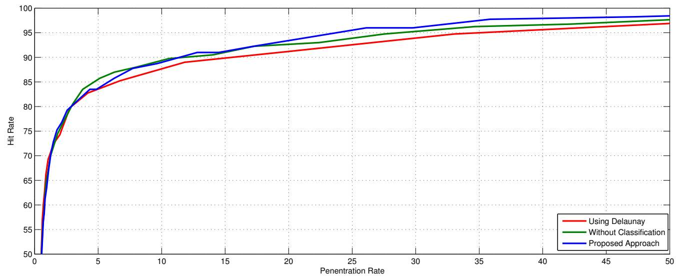


Figure 4.3: Hit Rate vs Penetration Rate Comparision for FVC-2002DB3

Various experiments were performed to evaluate the efficiency of our approach. We have conducted an experiment to test the efficiency of classifying the triangles into 8 classes. Obeservation from Fig (4.1) to Fig(4.7) shows that the lower penetration rate and higher hit were obtained by classifying the triangles. Without classification results were obtained by removing the classification from our approach. A two dimensional hash table was built using the similar approach.

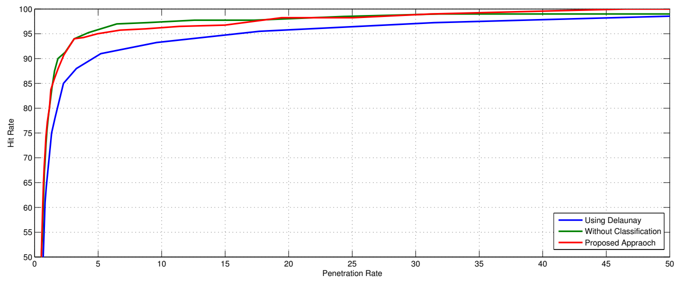


Figure 4.4: Hit Rate vs Penetration Rate Comparision for FVC-2002DB4

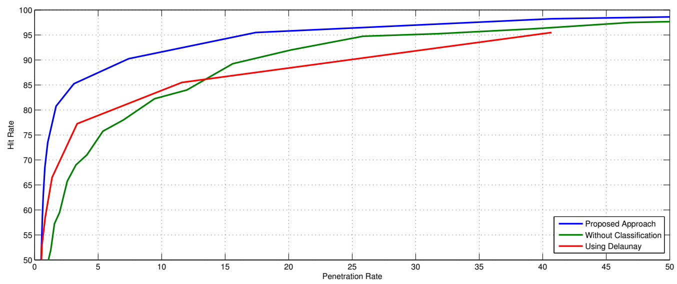


Figure 4.5: Hit Rate vs Penetration Rate Comparision for FVC-2004DB1

Another experiment was conducted to test the efficiency of using Extended set instead of Delaunay Triangulation. It can be concluded from figures(4.1) to (4.7) that using Extended Set produced more better results.

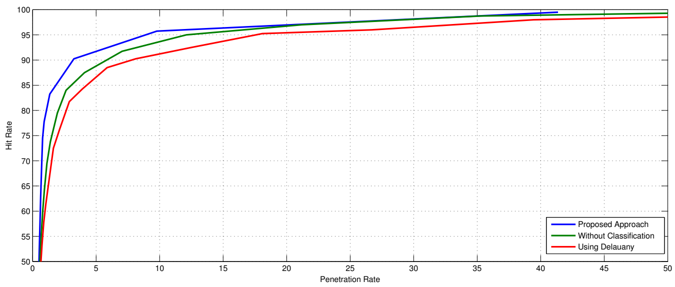


Figure 4.6: Hit Rate vs Penetration RateComparision for FVC-2004DB2

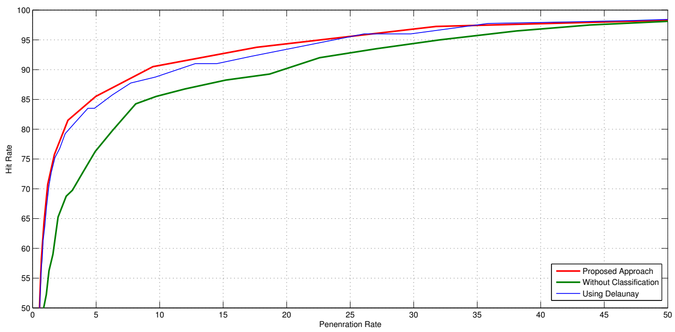
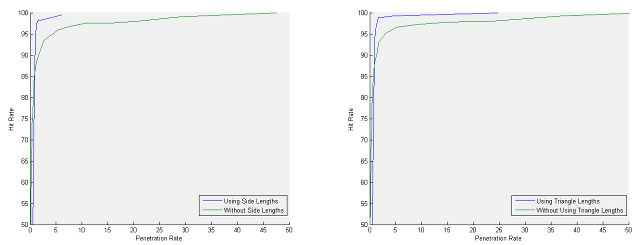


Figure 4.7: Hit Rate vs Penetration Rate Comparision for FVC-2004DB4

The last experiment was focussed on analising efficiency of using the lengths of the triangle. An experiment was conducted where we did not use the lengths of the triangle and the candidate list was computed based on the voting technique. During Verification step, while searching at the index in the hash table all the templates that are present in the index were given an vote. Fig(4.4) demonstrates that using lengths produce more better results.



(a) 2002DB1 (b) 2002DB2

Figure 4.8: Penetration rate vs Hit Rate comparision for using triangle lengths and using an voting technique

Fig (4.9) and Fig(4.10) shows the results of our approach when tested against FVC 2002 and

FVC 2004 database respectively.

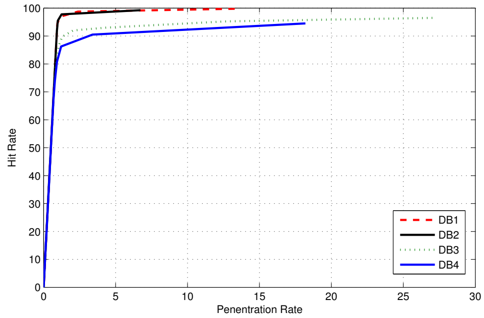


Figure 4.9: Hit Rate vs Penetration Rate for FVC-2002

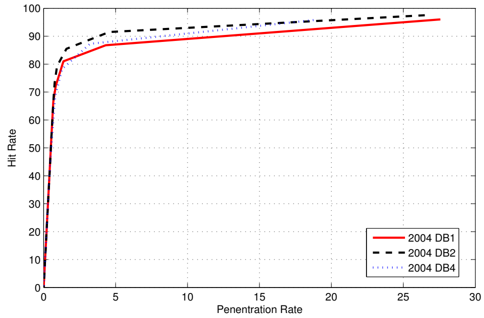


Figure 4.10: Hit Rate vs Penetration Rate for FVC-2004

4.2 Comparision with other related approaches

Approach	Hit Rate	Penetration Rate
R.Capelli et al,2011	99.5	15.5
A.Gago et al,2013	99.75	10
Our Approach	99.5	6.0325

Table 4.1: Comparision for FVC-2002DB1

Results obtained by our proposal have been compared with R.Cappelli et. al[7] and A.Gago et al[20].R.Capelli has used mintuia quadraplets instead of triplets. A.Gago has used Extended Set in is approach.We can see from table(4.1) that all of the approaches are considerably less accurate than our approach.

5 CONCLUSIONS

In this paper, a new fingerprint indexing approach based on minutia triangulation is proposed.The proposed approach uses a very robust triplet representation of minutia in its approach. Experimental results show that it can greatly reduce the number of candidate hypotheses for further verification.The obtained results shows that our approach outperforms the present state of art fingerprint appriaches

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