ATU: Adaptive Template Update for Constructive Fingerprint Identification

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Abstract

A fingerprint based human identification system attempts to determine identity of a query fingerprint by comparing it against all the stored template in the database. Performance of the system depends upon the quality of stored templates however, the template remains the same related to any particular identity throughout operation.

A fingerprint based recognition system gets many new fingerprint samples during its authentication. These samples are compared against the ones stored in database to decide upon the matching. Spatial distance between the database fingerprint template and the newly acquired one is a major reason for false rejection. This paper proposed a novel approach to utilize newly acquired fingerprint to constructively update fingerprint database to reduce spatial distance and to improve recognition accuracy. Experiments have been conducted upon widely used open fingerprint database FVC2002. Experimental results shows significant increase in the recognition accuracy.

1 Introduction

Biometrics facilitates an automated way of human recognition using their physiological and/or behavioral characteristics. It provides more security than the traditional authentication methods such as pin, passwords, access-card *etc.* because of having a strong binding between the user (human) and its biometric characters [1]. Biometric characteristics need not to be memorized and are hard to be carried off by an impostor. The process of biometric authentication starts by *registration* that acquire a new biometric sample of individual, process it, extract features (template creation) and label it with a unique identifier for the user. Extracted template is treated as a representative of user's identity. In *identification* phase, the system goes over to choose a person who is most likely to produce the same sample from the set of templates [12]. It is a well known fact that biometric features undergo temporal variations which include short term changes such as scars on fingerprint surface and long term changes like ageing or other temporary changes which include affine transformation in fingerprints. These variations severely degrade the performance of verification process and also, the enrolled samples become non-representative over a period of time[4]. Therefore, the solution lies in continuously improving the stored templates in the database for better adaptability and performance.

Template update *i.e.* making the biometric system adaptive to the template changes is a vital problem in a biometric recognition system. The standard solution to this problem is repeated recording of the biometric samples after a fixed interval of time. But this approach is quite expensive [10]. A taxonomy which classifies template update methods that are used to deal with on-going changes in the biometric samples is proposed in [5]. The author has categorized the methods as supervised and semi-supervised update methods. The basic difference in both the techniques lies in the approach followed for data labeling which is manual for supervised methods and automatic for semi-supervised technique. To reduce the cost due to supervised technique involving re-enrollment sessions, automated methods for template updating are preferred [3]. The drive behind following this practice is the availability of large input samples that are collected during system's operation. These samples which are usually discarded can be exploited to update the template automatically [8].

[11] propounded a minutiae based template adaptation algorithm which updates minutiae in a template after the authentication process by appending new minutiae points from the queried sample.

[2] proposed a semi-supervised method to update the biometric template, namely *self-update*. This technique amplify the template database with the input sample that has been collected during system's operation, provided the sample should be highly confidently classified i.e. its matching score with the already enrolled template is greater than an updating threshold. This technique is too much dependent on

setting up of threshold value [6]. On the other hand, [7] proposed a graph min-cut based approach which is independent of updating threshold and the experimental results show that it was able to acquire more number of samples with an indicative intra-class variations; hence, resulting in better updated templates. However, both of the techniques are susceptible to introduction of impostor into the updated template set. But, post processing has been found significant in reducing FAR of graph min-cut without affecting vulnerability.

Image mosaicing and feature mosaicing are two of the commonly used techniques for creating fingerprint mosaics. Minutiae based matching which is a feature mosacing has been found superior than image mosaicing [9] previously. An approach for fingerprint mosaicing using Thin Plate Spline transformation which accounts for the elastic deformation present in constituent fingerprint was significant in improving performance of fingerprint systems.

This paper proposes a novel algorithm that aims at continuously updating the biometric template stored in the database to account for the temporal changes that occur in biometrics and for better biometric recognition. Section 2 describes the proposed approach. Subsequent section discusses about the experimental setting, database used for experimentation and the obtained results. Conclusion and future scope are presented in the last.

2 Background

Thin Plate Spline: Thin plate spline transformation gets it's name from the physical analogy with the bending of a thin sheet of metal. In the metal sheet, the deformation is in the z axis, perpendicular to the sheet's plane. For applying this idea to the coordinate transformation problem, one can interpret the lifting of the plate as a displacement of the x or y coordinates within the plane. Thus, in general, two thin plate splines are needed to specify a two-dimensional coordinate transformation. The thin plate spline is the 2-D variant of the cubic spline in one dimension. It is the fundamental solution to the biharmonic equation, and which has the following form

$$U(r) = r^2 ln(r)$$

For a given a set of data points, a weighted combination of thin plate splines with it's center about each data point produces the interpolation function passing through the points exactly and minimizing "bending energy".Here, Bending energy is defined here as the integral over R2 of the squares of the second derivatives

$$\int \int_{R^2} ({f^2}_{xx} + 2{f^2}_{xy} + {f^2}_{yy}) dxdy$$

Regularization can be applied for relaxing the requirement of the interpolant passing through the data points exactly.

3 Proposed Approach

This section describes the methodology proposed by the authors for continuously updating the fingerprint database. First, the acquired fingerprint is preprocessed and features are extracted using mindtct from NIST fingerprint tools. The extracted template is pre-verified with the target template obtained from the database by the Minutiae Activator. It uses thin plate spline based matching and removes the noisy minutiae points from the acquired fingerprint template. These filtered minutiae points are then matched with the stored template using bozorth matching. Bozorth scores are then used to decide the acceptance or rejection of the match. If the scores are higher than Adaptation Threshold, the newly acquired template is used for feature improvement of the stored templates in the database. Block diagram of the proposed system is presented in Figure 1.

Image Acquisition: This is the first step done using special sensors called fingerprint scanner. One of the image acquired is shown in the Figure 2(a). Images used in this study are from the FVC 2002 DB2 database. These were capture using optical sensor "FX2000" by Biometrika at 569dpi resolution. The database has 8 samples per individual of 100 distinct persons.

Preprocessing: This is the second step which involves improvement of contrast and image enhancement using standard techniques. Corresponding images are as shown in Figure 2(b).

Feature Extraction: Features are extracted using `mindtct` utility of NBIS suite. `Mindtct` is based on a Multi-Layer Perceptron (MLP) based techniques as discussed in User's Guide to NIST Biometric Image

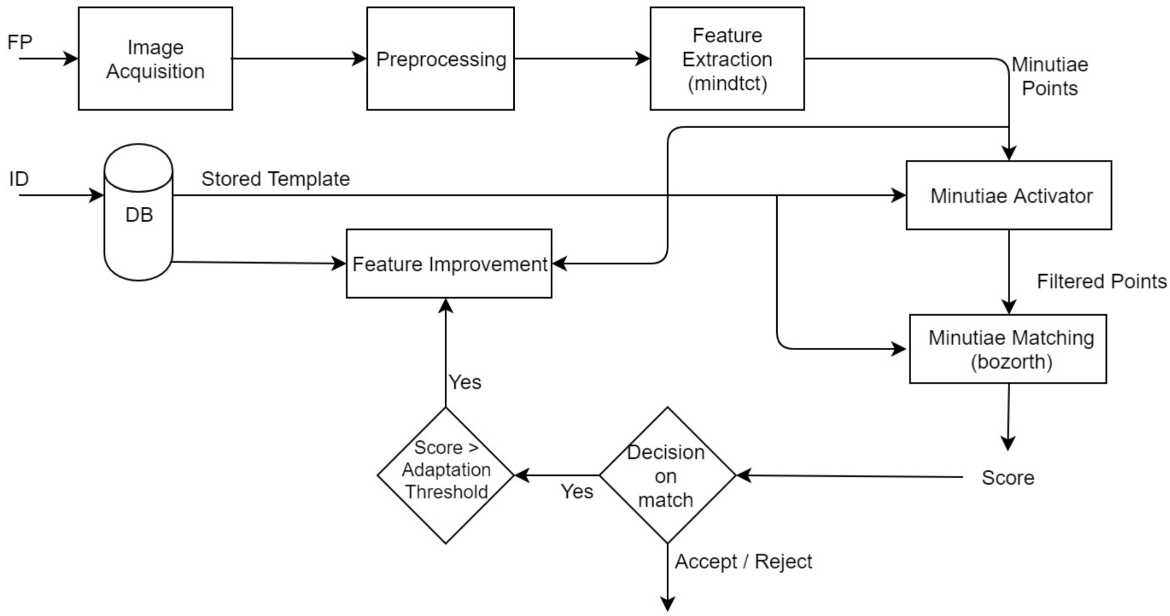


Figure 1: Block diagram of the proposed system.

(a) Raw Fingerprint Image from the sensor

(b) Preprocessed images

(c) Minutiae Extraction using `mindtct`

Figure 2: Fingerprint Feature Extraction

Software. The locations of minutiae points and their corresponding angles are as shown in Figure 2(c). It is must be noted that it has a lot of noise due to false minutiae detection as evident by the spurious minutiae outside the fingerprint region as well as at the edges of the fingerprint. These can potentially cause errors in detection and verification leading to degradation of performance. Hence this study focuses at removal of these noise points.

Minutia Activation System: Minutia Activation is the key stage of the process as it removes noise from the template in case of a potential correct match through high activation for true minutiae. It does not get strongly activated in case of spurious minutiae or impostor fingerprint templates resulting in reduction of noise points as well as a reduced false positive rate for impostors. Template A is chosen as test image and Template B is the image from database with respect to which it is to be compared. The is algorithm shown in Algorithm 1 and the same is described below

1. Consider a minutiae point m1 from template A and m2 from template B. Assume this pair to be matching and transform each minutiae in template B accordingly.

2. Count the number of matching minutiae pairs for each of the above combination of points. The combination with maximum number of points is considered as the best matching minutiae pair. Two

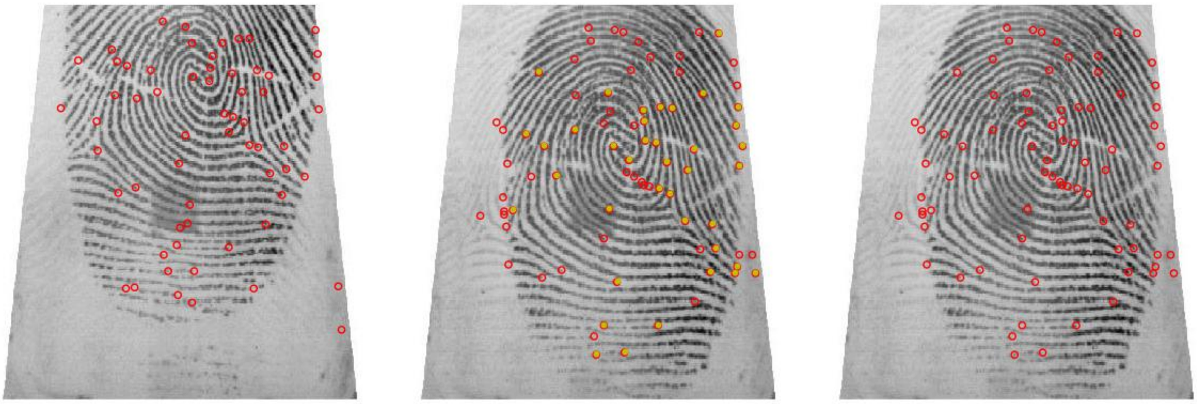


Figure 3: Initial matching of Template A with a correctly matching Template B. Image on the left is Template B which is the target, Template A is on the right and the central image shows the matching.

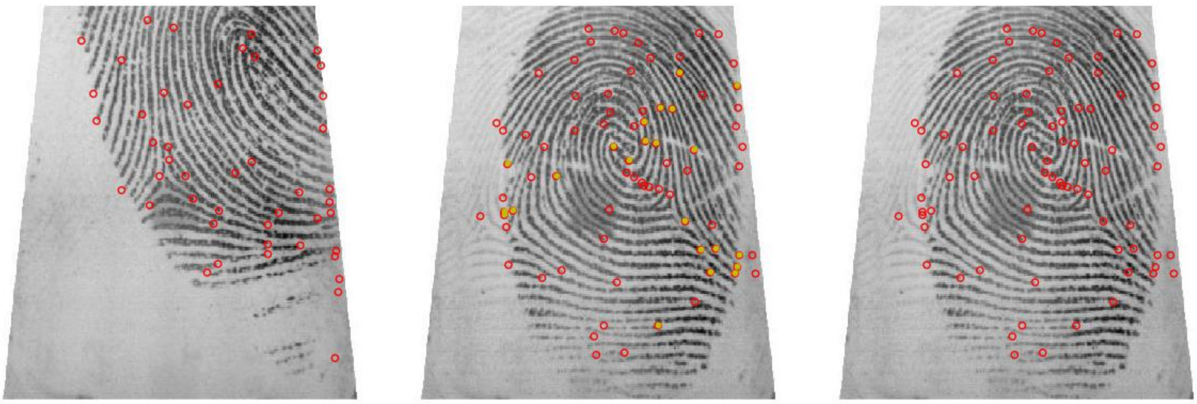


Figure 4: Initial matching of impostor Template A (right) with a different Template B (left) as shown in the central image.

minutiae from A and B are considered to be matching if the difference between their coordinates and theta is below a certain threshold.

3. Apply thin plate spline transformation on template B using the matching minutiae points of the best match as the control points. Thid warps the template B in a way similar to bending of a thin metal sheet. It attempts to negate the effect of the difference between applied non orthogonal forces when registering the fingerprint for templates A and B.

4. Repeat 1 to 3 on the given pair of templates until number of matching minutiae points attains a stable maxima. In a few cases with very less overlap between the fingerprint images, the initially transformed templates are used for mosaicing.

   The output for a correctly matching template pair is as shown in Figure 3. Notice that it has removed number of false minutiae significantly but has not been very successful in retaining the true minutiae points. This is because the thin plate spline was not able to accommodate completely for all the deformations. Figure 4 gives a typical case of impostor matching. Here the activation is weaker and hence only a few points match. This minor difference will get compounded in the next step proving the strength of out technique.

5. Repeat 1 to 4 for the first 4 templates of the actual fingerprint and when a minutiae match occurs increment it's confidence value.

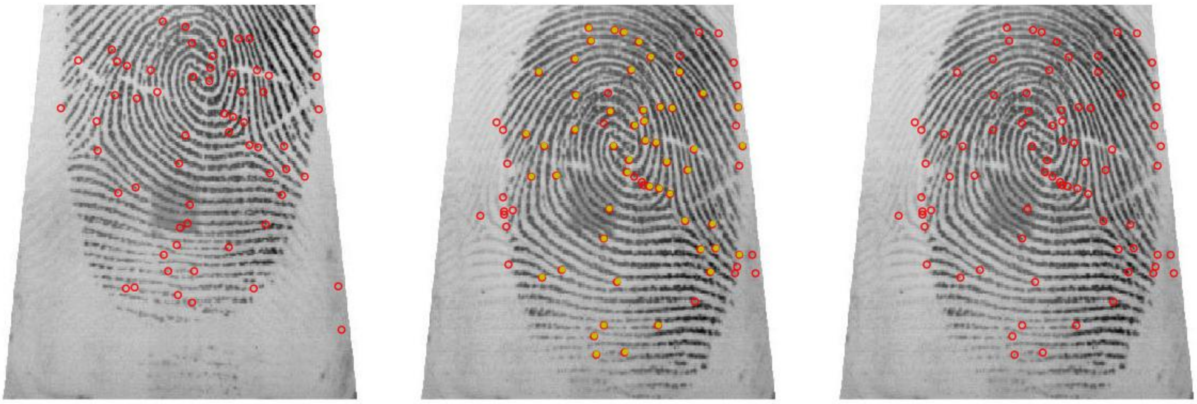


Figure 5: Final matching of Template A (right) with a correctly matching Template B (left) as shown in the central image.

Figure 6: Final matching of impostor Template A (right) with a different Template B (left) as shown in the central image.

6. For template A, retain the minutiae points with confidence value above the requisite threshold and remove the one's below to generate a preverified template.

7. Resulting preverified template after retaining points above the threshold are used for matching using `bozorth` utility of nbis. Figure 5 Figure 6 demonstrate outputs for correct match and impostor respectively. It is clear that the false minutiae points are mostly removed and a vast majority of the true minutiae are retained in case of correctly matching images. Whereas only a very few of the total points are left in the impostor template. This shows the effectiveness of our technique as it accounts for not just the similarity between two templates, but use the similarity between the test template and all the target templates present in the database. As a result there is a compounding effect of both false and true matches resulting high false minutiae removal and true minutiae retention as compared to techniques based on a pair of templates.

Minutia Matching: `bozorth` matching is performed on the resultant template of a test image with it's target image as obtained from Minutiae Activation stage. Number of activated minutiae points from the previous stage can be directly used as a similarity score between two fingerprint templates.

Algorithm 1: Minutia Activator

Input: *stablization_threshold*, *templateA*, *templateB*: number of matching minutiae takes a few iterations to stablize

Output: *templateBtrns*: Transformed B template for final comparison with A

```
for k = 1 to stablization_threshold do
    h_i = 1, h_j = 1, n_val = 0, B_trns = B
    for i ∈ minutiae(A) do
        for j ∈ minutiae(B_trns) do
            tranform btrns geometrically w.r.t i,j as matching points
            n_ij = number of matching minutiae after transform if n_ij > n_val then
                h_i = i, h_j = j

        end
        transform geometrically B_trns w.r.t to h_i, h_j
        control_points = points matching after above transformation
        B_trns = thin plate spline tranformation of B using above control_points
    end
end
return B_trns.
```

4 Results

4.1 Database

FVC 2002 database, which is a standard in the research domain having 8 fingerprint samples for each of the 100 users has been used here. Initially randomly selected subset of 25 fingerprints from the set of 100 has been used for faster processing times. Then the entire database has been used for benchmarking of the best results obtained from the subset.

4.2 Evaluation Parameters

The thresholds for distance, relative angle and number of minimum matches for accepted minutiae are varied and their effects on Correct Recognition Rate and Equal Error Rate for verification task are studied.

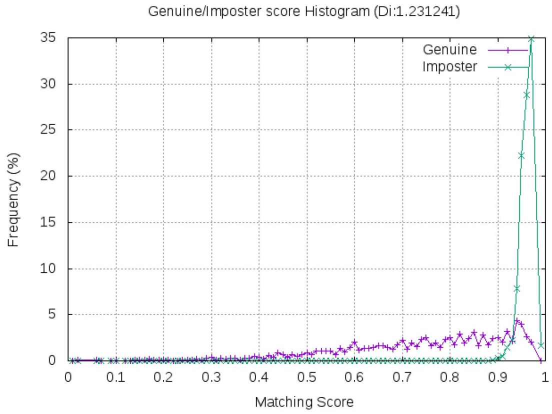
4.3 Observations

S.No.	Experiment	d	θ	$\#min$	CRR	EER
1.	`bozorth` matching on fingerprint template extracted using `mindtct`	-	-	-	**96.00**	9.44
2.	Mosaiced first 2 images of each fingerprint into a single composite mosaic	4	8	2	3.25	42.50
3.	Mosaiced first 4 images of each fingerprint into a single composite mosaic	4	8	3	4.62	32.45
4.	Removed possible noise by placing other 3 template on each template	4	8	2	44.75	34.06
5.	Removed possible noise by placing other 3 template on each template	4	8	3	41.50	34.09
6.	Base for 25 users (randomly selected)	-	-	-	**82.00**	18.51
7.	Pre-verification of test templates on first two images of each fingerprint for 25 users	4	8	2	63.00	25.53
8.	Pre-verification of test templates on first two images of each fingerprint for 25 users	4	8	3	63.00	27.59
9.	Pre-verification of test templates on first four images of each fingerprint for 25 users	3	6	2	63.00	25.86
10.	Pre-verification of test templates on first four images of each fingerprint for 25 users	3	6	3	64.00	28.35
11.	Using minutiae activation followed by bozorth matching for 25 users	8	12	2	6.00	41.73
12.	Using minutiae activation followed by bozorth matching for 25 users	8	12	3	7.12	29.93
13.	Using minutiae activation based matching for 25 users	8	12	2	88.00	22.33
14.	Using minutiae activation based matching for 25 users	8	12	3	**100.00**	20.68
15.	Using minutiae activation based matching for 100 users	8	12	2	73.00	25.36
16.	Using minutiae activation based matching for 100 users	8	12	3	**100.00**	20.02

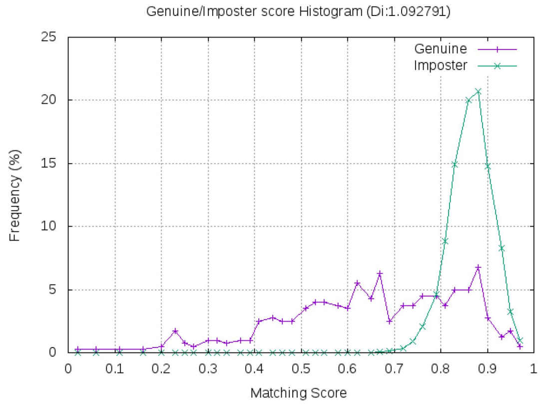
Baseline CRR for templates for 100 individuals which were `mindtct` extracted and compared using `bozorth` was found to be 96.00 with an EER of 9.44 as in 1. Removal of noise with the strict thresholds as in 2. doesn't help improve the accuracy. Base accuracy for the randomly chosen subset of 25 individuals is found to be 82 percent with EER of 18.51. Pre-verification using either two or four images at distance threshold of 3 and theta of 8 have CRR of 63.00 and 64.00 percent respectively. Using activated minutiae templates for bozorth matching leads to a system collapse with a CRR of 6 percent and EER of 12 percent at distance threshold of 8 and theta of 12 along with atleast two matching points. Increasing matching threshold to 3 doesn't help much giving a CRR of 7.12 and EER of 22.33. Possible reason is for this behavior can be that bozorth gets only closely matching minutiae templates even for impostors reducing the discriminating power of the model. Breakthrough is achieved when minutiae activation is used as an independent matching technique. Number of matched minutiae is used as a similarity score between two templates. In this case a CRR of 88 and EER of 20.68 is achieved using distance, theta and match thresholds of 8, 12 and 2 respectively. Increasing the match threshold to 3 makes the system more robust giving it CRR of 100 and EER of 20.68. Applying this technique to entire database of 100 users has resulted in CRR of 100 and EER of 20.02 beating the baseline CRR of 96 with an impressive margin and providing a fully accurate matching system.

4.4 Results

This section describes the results obtained by using Minutiae Activation as a matching system on the entire database of 100 images. This achieves a CRR of 100 and EER of 20.02 as discussed priorly. Figure 7 shows the Histogram of genuine and impostor scores for Bozorth Matching of the dataset images as well as Minutiae Activation based matching. Receiver operating characteristics (ROC) curve shows the relationship between false acceptance and false rejection rate. We have produce four kinds of ROC

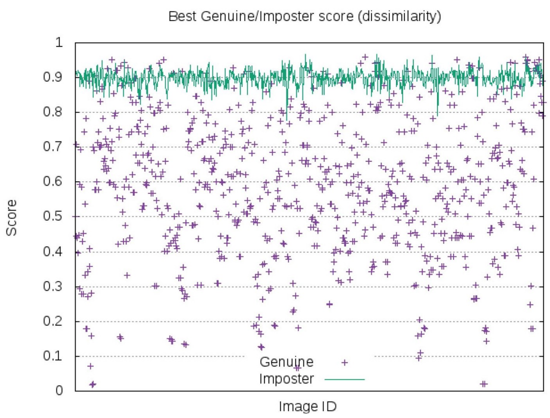


(a) Bozorth Matching

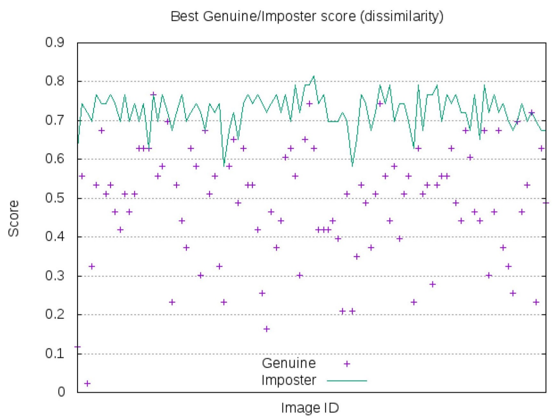


(b) Minutiae Activation Matching

Figure 7: Histogram of genuine and impostor scores.

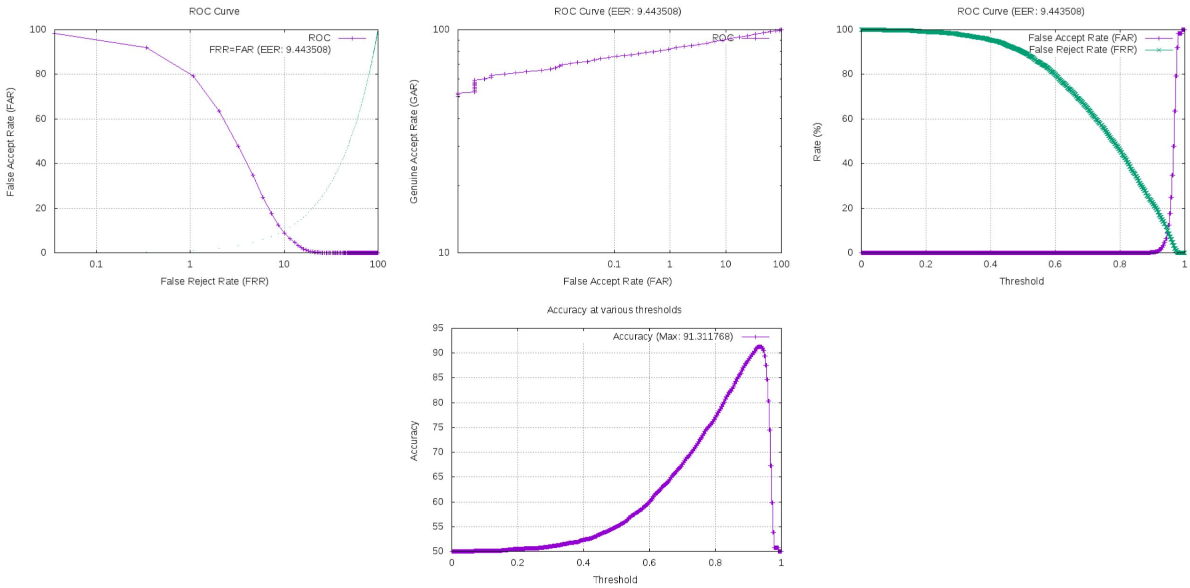


(a) Bozorth Matching

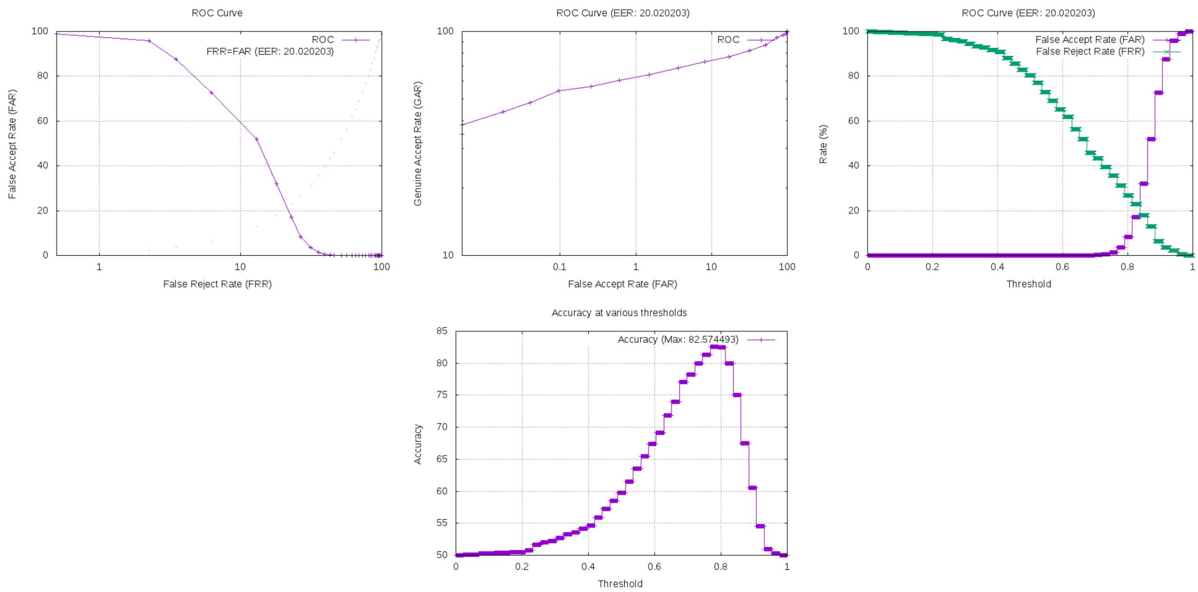


(b) Minutiae Activation Matching

Figure 8: Best genuine and impostor scores for every image in training set.



(a) Bozorth Matching



(b) Minutiae Activation Matching

Figure 9: Curves showing ROC and Accuracy.

curves in Figure 9 for the baseline as well as the proposed system. For the proposed system the area under the ROC curve (EUC) is 11.798564. Equal error rate (EER) of the system is 20.020203 which is taken at the threshold:0.813953 where the values of false acceptance rate and false rejection rate are closest. Observed value of false acceptance rate (FRR) and false rejection rate (FAR) is 23.000000 and 17.040405 respectively at this threshold. Difference between FAR and FRR at this threshold is found to be 5.959595 which is minimum across all the thresholds. For every training image we choose only two of its matching scores out of the n-1 available. First one is the minimum of all its impostor matchings and second one is the minimum among all genuine score. Using these scores we create a new matching file and produce the results. Figure 8 shows best genuine and best impostor score for every training image. It must be noted that for the bozorth matching system all 4 templates of a user present in the database are treated separately while they are treated as a single data point in the proposed system.

5 Conclusion

Minutiae activation is a unique technique which can be applied to different stages of a minutiae matching system. It is very effective when used a matching technique by itself and provides better than baseline scores. However using minutiae activated templates for bozorth matching reduces system performance drastically because only closely matching minutiae are left leading to high bozorth scores for even impostors. Minutiae activator can be potentially used for removing falsely detected minutiae as illustrated in this work. There is great potential for future work with this technique owing to it's promising performance as a matching technique delivering a perfect CRR of 100 percent for the dataset used. It can be used as an ensemble with other matching techniques to get better performance in real implementations.

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