False Minutiae’ Impact on Fingerprint Matching: An Investigative Study

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Abstract—This paper presents a report on the investigative study of the impact of false minutiae on the performance of fingerprint matching systems. A 3-tier algorithm comprising of pre-processing, minutiae extraction and post-processing stages formed the backbone of the experiments. The pre-processing stage enhanced the fingerprint image, the minutiae extraction stage used the minutiae properties to detect and extract true and false minutiae points while the post-processing stage eliminated the false minutiae points. The experiments were performed on the four datasets in each of the three standard fingerprint databases; namely FVC2000, FVC2002 and FVC2004. The completion times for the minutiae extraction and the post-processing algorithms on each dataset were measured. A standard fingerprint matching algorithm was also implemented for verifying the impact of false minutiae points on FAR, FRR and the matching speed. Analysis of the obtained results revealed that for reliable and optimal performance of fingerprint matching systems, false minutiae points must be eliminated as much as possible from their operations.

Keywords—Fingerprint, minutiae point, AFIS, experimental study, fingerprint databases, fingerprint matching

I. INTRODUCTION (HEADING 1)

Automated Fingerprint Identification System (AFIS) is a device for human verification and identification in places or centres where human traffic management and control are required [1-3]. The recent upsurge in the acceptance and use of AFIS over the other biometrics-based devices has been attributed to a number of factors which include:

a. Fingerprint exhibits properties that are highly unique from individual to individual
b. It is possessed by every individual
c. It maintains durable and consistent form in one’s lifetime
d. There are a wide range of low-cost devices and technologies for fingerprint enrolment and processing

The steps involved in the operation of an AFIS are conceptualized in Figure 1. For consistent and reliable performance, trust worthy matching or rejection results must be obtained. Very low False Acceptance Rate (FAR) and False Rejection Rate (FRR) are also expected for users’ acceptability and patronage. To achieve these objectives, suitable and reliable algorithms must form the backbone of these steps.

Sequential to fingerprint image enrolment, several enhancement activities including pre-processing, segmentation, normalization and image filtering are performed. Local variance and angular definitions constitute the method for fingerprint segmentation to separate the fingerprint foreground from its background. Normalization is also performed for standardization of the ridge grey level values [4]. Several methods including Gabor filter [5-10], Short Time Fourier Transform [11] and Directional Filter [12-14] are some of the most popular approach to filtering fingerprint ridge and valley patterns in gray levels. At the fingerprint enhancement stage, all the noises and the contaminants introduced during enrolment are removed to pave way for a smooth and accurate minutiae extraction. The extracted minutiae then formed the reference minutiae set that is matched with pre-created minutiae sets in the template database. Commonly used minutiae are the end points (enclosed in circles) and bifurcations (enclosed in square) in Figure 2 [15-19]. The ridge terminates at the end point while it splits into two at the bifurcation point.

Based on specified algorithm, the characteristics (orientation, coordinate and distance relative to singular points) for the minutiae set of an image is compared (matched)
with those for other images to establish or reject claim of identity. The implementation of very safe and reliable fingerprint minutiae extraction strategies is therefore important for ensuring accuracy [16-18]. Existing research works on fingerprint minutiae extraction include the use of Adaptive Flow Orientation [19-20], Mathematical Morphology [21-22], Ridge Tracing [23-24], Fuzzy Image [25] and Complex filtering [26-27]. Others are Weighted Audio Spectrum Flatness-WASF [28], Stochastic Resonance [29], Cellular Neural Networks [30] and Pseudo Zernike Moments [31]. Section 2 of this paper focuses on review of relevant literature while Section 3 presents fingerprint minutiae extraction technique. Sections 4 and 5 present the experimental study and the conclusion respectively.

II. LITERATURE REVIEW

Several techniques have emerged for fingerprint minutiae extraction with their respective strengths and weaknesses. The authors in [29] presented a stochastic resonance approach for feature extraction from low-quality fingerprints. Gaussian noise was added to the original fingerprint images earlier rejected due to low-quality by some state-of-the-art fingerprint verification algorithms before extraction. Though, the approach failed with fingerprints with no meaningful features, obtained results showed significant improvement in the equal error and genuine acceptance rates. The authors in [23] presented an algorithm for minutiae extraction from skeletonized and binarized images. An algorithm was also proposed for ridge cleansing based on ridge positions and directional maps. The obtained results showed efficient reduction of spurious minutiae with good performances in dirty areas but the algorithm experiences low processing speed due to computational complexity. The authors in [24] proposed an algorithm for the extraction of fingerprint features from gray scale images by ridge tracing which used contextual information to handle noisy regions with used parameters made adaptive for circumventing human supervision. The algorithm is suitable for speedy extraction of minutiae points but susceptible to extraction of type-exchange minutiae as well as dropped features like short ridges and spurs. Mathematical morphology algorithm is used in [21-22] to remove the superfluous information for genuine feature extraction and measure performance through sensitivity and specificity. The algorithm effectively removed spurious structures and extracted clear and reliable ridge map from input fingerprint image but experienced a number of missed genuine minutiae. A set of local feature descriptors for fingerprints is proposed in [26]. Minutiae points are detected through a complex filtering of the structure tensor by revealing their positions and directions. Model formulation was by parabolic and linear symmetry descriptions for the extraction of local features and their ridge orientations and reliabilities. Although results on their application in several stages of fingerprint recognition systems showed efficiency, the descriptors failed with severely distorted images. The authors in [30] proposed Cellular Neural Networks (CNN) algorithm for the extraction of high percentage of genuine feature points and their corresponding direction attributes from thinned fingerprint images. The algorithm rejects spurious feature points resulting from noisy fingerprints, but show low computational speed due to un-optimized procedures. A fingerprint local invariant feature extraction using Feature Transform (SIFT) and Speeded-Up Robust Feature (SURF) detectors is proposed in [32]. The detectors run on the central and graphic processing units and focus on the consumed time as important factor for fingerprint identification. The implementations produced promising behaviours for the two detectors with very short processing time.

A method for direct extraction of features from gray-level fingerprint images without binarization and thinning is proposed in [33]. The algorithm traced the ridges, recorded the skeleton image and acquired minutiae with robustness and efficiency. The authors in [15, 17] used Crossing Numbers (CN) algorithms that is based on ridge scanning for fingerprint minutiae extraction. For bad quality image, the algorithm is prone to extraction of exceeding number of false minutiae prompting the authors in [15] to use a post-processing stage to eliminate all forms of spurious features using their ridge and neighbourhood characteristics. A features detection method which reduces the likelihood of an unreliable overlapping region in partial fingerprint is proposed in [34]. The method provides significant improvement for matching low quality images but fails with too much overlapping areas.

A Gabor filter-based method for direct extraction of fingerprint minutiae from grey-level images without pre-processing is proposed in [35]. The method demonstrated efficiency and suitability than other conventional methods but failed with images whose grey-level cannot be determined. The algorithm solved some fingerprint recognition problems relating to translation, scaling and rotation. The authors in [25, 36] implemented algorithms for high level minutiae extraction for all fingerprint images based on pre-processing stages (singular point detection, orientation field estimation and Gabor filter). The performance of these algorithms however depends on the precision of directional and frequency maps. The authors in [31] presented invariant fingerprint minutiae extraction algorithm based on Pseudo Zernike Moments [37-38] and Bayelsian classifier [39].

Figure 2: Fingerprint ridges showing end and bifurcation points

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III. FINGERPRINT MINUTIAE EXTRACTION TECHNIQUE

The algorithm that formed the basis of minutiae extraction experiments is conceptualized in Figure 3 showing the pre-processing, minutiae extraction and validation stages.

A. Image Pre-Processing

For smooth and reliable minutiae extraction, the enrolled fingerprint image is taken through a pre-processing stage of enhancement. The stage includes segmentation, normalization, ridge orientation and frequency estimation, filtering, binarization and thinning. The essence of segmentation is to clearly divide the background region from its foreground region. The background regions generally exhibit high noise and contaminant levels as well as very low grey-scale variance values. On the contrary the foreground regions possess very high variances with minimal noise and contaminants. Based on these characteristics, variance thresholding technique is used to separate the background from the foreground regions. The first step of the technique is a division of the image into blocks followed by the calculation of the grey-scale variance for each block. A block with variance exceeding the global threshold is assigned to the foreground otherwise it is assigned to the foreground. The grey-level variance for a block, \( b \) with size \( \beta \times \beta \) is defined as [4, 40]:

\[
\sigma(b) = \sigma^{-2} \sum_{m=0}^{\beta-1} \sum_{n=0}^{\beta-1} V
\]

\[
V = (B(m, n) - \mu(b))^2
\]

\( \sigma(b) \) is the variance for block \( b \), \( B(m, n) \) is the grey-level value at pixel \( (m, n) \), and \( \mu(b) \) is the mean grey-level value for the block \( b \).

The segmented image is normalised by regulating its grey-level values to attain uniformity and fall within desired range. If \( \rho(r, s) \) represents the grey-level value at pixel \( (r, s) \), and \( \beta(r, s) \) represents the normalised grey-level value at pixel \( (r, s) \), the normalised image is derived from:

\[
\beta(r, s) = \begin{cases} 
\gamma_0 + \sqrt{(\theta_0(\rho(r, s) - \gamma)^2)\theta^{-1}} & \text{if } \rho(r, s) > \gamma \\
\gamma_0 - \sqrt{(\theta_0(\rho(r, s) - \gamma)^2)\theta^{-1}} & \text{otherwise}
\end{cases}
\]

\( \gamma \) and \( \theta \) are the calculated mean and variance of \( \rho(r, s) \), respectively while \( \gamma_0 \) and \( \theta_0 \) are the desired mean and variance respectively.

The orientation field of a fingerprint image gives the local orientation of its ridges. It is computed by dividing the image into blocks of uniform sizes and the local orientation for a block with centre at pixel \( (r, s) \) is computed from [40–42]:

\[
V_x(r, s) = \frac{1}{2} \sum_{p=r-w}^{r+w} \sum_{q=s-w}^{s+w} 2\partial_x(p,q)\partial_y(p,q)
\]

\[
V_y(r, s) = \frac{1}{2} \sum_{p=r-w}^{r+w} \sum_{q=s-w}^{s+w} \partial_x^2(p,q) - \partial_y^2(p,q)
\]

\[
\theta(r, s) = \frac{1}{2} \tan^{-1} \frac{V_y(r, s)}{V_x(r, s)}
\]

\( \partial_x(p,q) \) and \( \partial_y(p,q) \) are the gradients obtained using sobel operator at point \( (p,q) \) in x and y directions respectively. \( \theta(r, s) \) is the least square estimate of the local orientation of the block with centre at pixel \( (r, s) \).

The ridge frequency estimation algorithm produces a coarse-level ridge map of the input fingerprint image and it is based on pre-estimated local ridge orientations. Grey levels along fingerprint ridges and valleys are modelled as sinusoidal shaped wave along the normal direction to the local orientation. The wave is principally utilized for the estimation of the ridge frequency based on the assumptions that valid ridge frequencies lie between 1/31 and 1/25 for 500dpi images [6, 43–44]. Fingerprint image filtering is based on the periodic function \( G(x, y; f, \theta) \) as follows [8]:

\[
G(x, y; f, \theta) = \exp \left[ 0.5 \left( \frac{\alpha^2 \partial_x^2 + \beta^2 \partial_y^2}{\partial_x \partial_y} \right) \right] \cos(2\pi f u)
\]

\[
\alpha = x\sin\theta + y\cos\theta
\]

\[
\beta = x\cos\theta + y\sin\theta
\]

\( f \) represents the frequency of the sinusoidal plane wave along the direction \( \theta \) from the x-axis, and \( \partial_x \) and \( \partial_y \) are the space constants empirically determined and set to about half the average inter-ridge distance in their respective direction. The filtered image is binarised using the method proposed in [45] to obtain its best performance threshold. The threshold (T) is set for making each cluster as tight as possible, thereby minimizing their overlap. T is determined by separating the pixels into two clusters based on presumed thresholds and the mean of each cluster is determined. The difference between the means is squared and the product of the number of pixels in one cluster and the number in the other is determined. The success of these operations is determined by the difference between the means of the clusters while the optimal threshold maximizes the between-class variance or minimizes the within-class variance. The binarised image is thinned with the Matlab ‘bwmorph’ operation using the ‘thin’ option to generate the thin or skeleton image.

Figure 3: Fingerprint filtering stages
B. Minutiae Extraction

During minutiae extraction, a fingerprint image is viewed as a flow pattern with a definite texture from which an orientation field for the flow texture is computed [46]. From a filtered (thinned) image, a minutia point is extracted based on its CN value obtained from:

\[
CN = \sum_{i=0}^{7} |N_{i+2} - N_{i+1}|, \quad N_0 = N_4
\]

Here, \( N_1, N_2, \ldots, N_8 \) represent the 8 neighbours of the candidate minutia point \( N \), in its 3 x 3 neighbourhood which are scanned in the direction shown in Figure 4.

Table 1 shows the existing CN properties with 2 and 6 denoting ridge end and bifurcation points respectively. These two points are considered as the true minutiae points. The isolated, continuous and crossing points produced spur, hole, triangle and spike structures which are all regarded as false minutiae points. As shown in Figure 5, the spur structure generates false ridge endings while the hole and triangle structures produce false bifurcations. The spike structure also creates a false bifurcation and a false ridge ending point [15, 41, 47]. Figure 6 shows a candidate ridge pixel (at the centre of the enclosed ridges) for ridge ending and bifurcation points.

![Figure 4: A candidate point and its 8 neighbours](image)

![Figure 5: False Minutiae Structures](image)

![Figure 6: CN values for ridge ending and bifurcation points](image)

C. Post-Processing

For the elimination of all forms of false minutiae extracted by the CN algorithm, a post-processing or validation algorithm [15, 20, 40] is implemented. The flowchart of the algorithm is presented in Figure 7. It tests the validity of each candidate minutia point by scanning the skeleton image and examines its local neighbourhood. An image \( M \) of size \( W \times W \) centered on the candidate minutia point is firstly created and its central pixel is labelled with CP while the remaining pixels are initialised to zero. Other connecting point is labelled with 1 and 3 for ridge end and bifurcation points respectively as shown in Figure 8.

![Figure 7: Flowchart for minutiae validity test](image)

![Figure 8: 0 to 1 transitions. (a) Bifurcation (\( T_{01}=3 \), (b) Ridge ending (\( T_{01}=1 \))](image)

IV. EXPERIMENTAL STUDY

The experiments based on Matlab application were carried out using FVC2000, FVC2002 and FVC2004 standard fingerprint databases on Ms-Window 7 Operating System on a Pentium 4 – 2.80 GHz dual processors with 4.00GB of RAM. The summary of the three standard databases is presented in Table I: CN Number and Its Property.
Table II [48–49]. The three databases were jointly formulated by the Biometric System Laboratory of the University of Bologna, together with the Biometric Test Centre of the San Jose State University and the Pattern Recognition and Image Processing Laboratory of the Michigan State University. There are four datasets in each of the three databases and each dataset has 80 fingerprints of different qualities and obtained at different resolution, orientation and sizes on the basis of 8 enrolments from each of 10 different people.

Figures 9(d), 9(e) and 9(f) present the extracted minutiae based on CN algorithm from the skeleton (thinned) images of Figure 9(a), 9(b) and 9(c) respectively. The true ridge ends are shown with circles (red colour), the square marks (blue colour) represent the true bifurcation points and the false minutiae points are denoted with diamonds (in green). The ratio of true to false ridge end points extracted and shown in Figure 9(d), 9(e) and 9(f) are 19:13, 25:14 and 26:13 respectively. For bifurcation points, the ratio is 13:7, 6:13 and 9:19 respectively. The results from the minutiae extraction experiments on the three standard fingerprint databases using the CN algorithm are presented in Table III. Higher values are recorded for false minutiae points over true minutiae points in all cases. As shown in Figures 10 and 11, there are higher percentages for false ridge end and bifurcation points in all the datasets and databases.

The exceedingly higher number of extracted false minutiae points is attributed to the presence of high cases of corrupted

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**TABLE II: DETAILS OF THE STANDARD FINGERPRINT DATABASES**

<table>
<thead>
<tr>
<th>Database</th>
<th>Sensor Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>FVC2000</td>
<td>Optical Sensor</td>
</tr>
<tr>
<td>FVC2002</td>
<td>Capacitive Sensor</td>
</tr>
<tr>
<td>FVC2004</td>
<td>Optical Sensor</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Image size</th>
<th>No.</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB1</td>
<td>300 x 300</td>
<td>388</td>
<td>640 x 480</td>
</tr>
<tr>
<td>DB2</td>
<td>256 x 354</td>
<td>296</td>
<td>328 x 364</td>
</tr>
<tr>
<td>DB3</td>
<td>448 x 478</td>
<td>300</td>
<td>300 x 480</td>
</tr>
<tr>
<td>DB4</td>
<td>240 x 320</td>
<td>288</td>
<td>288 x 384</td>
</tr>
</tbody>
</table>

**TABLE III: STATISTICS OF EXTRACTED TRUE AND FALSE MINUTIAE FROM THE THREE DATABASES**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>FVC2000</th>
<th>FVC2002</th>
<th>FVC2004</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>Time(s)</td>
<td>Total</td>
</tr>
<tr>
<td>DB1</td>
<td>Ridge end</td>
<td>10683</td>
<td>91.86</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>6254</td>
<td>95.45</td>
</tr>
<tr>
<td>DB2</td>
<td>Ridge end</td>
<td>7914</td>
<td>97.05</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>8008</td>
<td>97.83</td>
</tr>
<tr>
<td>DB3</td>
<td>Ridge end</td>
<td>54165</td>
<td>231.34</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>46681</td>
<td>156.76</td>
</tr>
<tr>
<td>DB4</td>
<td>Ridge end</td>
<td>6269</td>
<td>73.35</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>8147</td>
<td>12873</td>
</tr>
</tbody>
</table>

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Figure 9: Fingerprint images from standard databases and their true and false minutiae points

Figure 10: Percentage of true and false extracted ridge ends

The detailed results for the pre-processing sub-stage of segmentation, normalization, filtering, binarization and thinning had been discussed in [50] and they are excluded from this report. Formatted images from datasets DB1 of FVC2000, FVC2002 and FVC2004 standard databases are shown in Figure 9 (a), 9(b) and 9(c) respectively.

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regions in several of the images. The corrupted regions resulted in the introduction of a great number of artifacts during enhancement [3] some of which appear in form of ridge ends while others as bifurcations. In Figure 12, a highly corrupted image in dataset DB3 of FVC2000 fingerprint database is presented with its extracted true and false minutiae points. It is revealed how the false minutiae points (marked with ‘X’) with numerous overlaps, outnumbered the true minutiae points (shown in circles and squares). A total of 123 false minutiae extraction is recorded as against 59 for true minutiae points.

Since different enrolment (from same or different fingers) experience different level of corruption (noise and contaminations), it is therefore consequential that different number of true and false minutiae points will be generated for different images. It also implied that the extraction of different number of false minutiae from images of the same finger will pose a great challenge to reliable implementation of AFIS. Using a window size of 23 x 23, the post-processing algorithm experiments were used to achieve total elimination of all false minutiae points and the results for Figures 9(d), 9(e) and 9(f) are shown in Figure 13(a), 13(b) and 13(c) respectively. The summary of the results of the elimination of all false minutiae points from the images in the three databases are presented in Table IV. The summary shows very significant reduction in the number of extracted minutiae but increase in the completion time when compared with Table III. The increase in the completion time is the time for the extra effort of validating or rejecting a minutia point.

Window size exceeding or below the stated value showed some deficiencies in the elimination of the false minutiae points [15]. When the window size is higher, some false minutiae points are extracted while lower value led to the non-extraction of some valid minutiae points.

Experiments were also conducted for the evaluation of the impact of the false minutiae points on fingerprint matching. Based on the algorithm proposed in [51], false rejection and acceptance rates experiments were performed on fingerprints in the three databases. The false acceptance experiments measured the rate at which images from different fingers are found to match (matching value exceeding threshold). The false rejection experiments also measured the rate at which images from same finger failed to match (matching value falling below threshold). In all the datasets, matching experiments based on minutiae extracted using CN algorithm (which produced true and false minutiae) in one hand and post-processing algorithm (which produced only true minutiae points) on the other hand, resulted in False Acceptance Rate (FAR) of 0%. The trend of obtained False Rejection Rate (FRR) results for the two sets of experiments is presented in Figure 14. The lower FRR values for true minutiae-based matching indicate there is greater accuracy, reliability and efficiency when false points are eliminated from the minutiae set. The higher FRR values for matching inclusive of false minutiae points imply that the presence of false minutiae points is capable of worsening the performance of a fingerprint matching algorithm.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>FVC2000</th>
<th>FVC2002</th>
<th>FVC2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB1</td>
<td>Ridge end</td>
<td>4042</td>
<td>99.88</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>1675</td>
<td></td>
</tr>
<tr>
<td>DB2</td>
<td>Ridge end</td>
<td>2966</td>
<td>104.15</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>2197</td>
<td></td>
</tr>
<tr>
<td>DB3</td>
<td>Ridge end</td>
<td>14200</td>
<td>254.38</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>9694</td>
<td></td>
</tr>
<tr>
<td>DB4</td>
<td>Ridge end</td>
<td>2442</td>
<td>79.86</td>
</tr>
<tr>
<td></td>
<td>Bifurcation</td>
<td>2223</td>
<td></td>
</tr>
</tbody>
</table>

Figure 11: Percentage of true and false extracted bifurcations

Figure 12: Fingerprint image and its extracted true and false minutiae points

Figure 13: Results showing the elimination of false minutiae
The completion times (in seconds) for FAR and FRR experiments on the 80 fingerprint images in each of the datasets for every standard database are shown in Tables V and VI. Based on the figures presented on these Tables, the line plots of Figure 15 and 16 clearly show the very wide gaps between the computation times for FAR and FRR in the CN and post-processing algorithms-based experiments. The lower completion times for the post-processing-based experiments are attributed to lower number of minutiae searches and minimum computations. Statistical analysis of the values presented in Tables V and VI also revealed that matching inclusive of false minutiae points take about 3.5, 3.29 and 2.86 times the time for true minutiae-based matching for all the datasets in FVC2000, FVC2002 and FVC2004 standard databases respectively. It is therefore obvious that the elimination of all false minutiae points at the feature extraction stage in a fingerprint pattern matching system is a necessity for reliable, high speed and user friendly operation.

| TABLE V: COMPLETION TIME (IN SECONDS) FOR TRUE MINUTIAE-BASED FINGERPRINT MATCHING |
|---------------------------------|-----------------|-----------------|-----------------|
|                                | FVC2000         | FVC2002         | FVC2004         |
| FAR                             | FRR             | FAR             | FRR             | FAR             | FRR             |
| DB1                             | 12.62           | 11.51           | 15.33           | 14.65           | 13.14           | 12.36           |
| DB2                             | 14.11           | 12.37           | 21.92           | 18.31           | 16.70           | 14.21           |
| DB3                             | 15.90           | 14.52           | 22.91           | 21.33           | 15.01           | 15.32           |
| DB4                             | 11.73           | 13.57           | 12.34           | 17.95           | 12.62           | 14.94           |

| TABLE VI: COMPLETION TIME (IN SECONDS) FOR FINGERPRINT MATCHING INCLUSIVE OF FALSE MINUTIAE |
|---------------------------------|-----------------|-----------------|-----------------|
|                                | FVC2000         | FVC2002         | FVC2004         |
| FAR                             | FRR             | FAR             | FRR             | FAR             | FRR             |
| DB1                             | 44.17           | 40.28           | 50.43           | 48.19           | 37.58           | 35.34           |
| DB2                             | 49.38           | 43.29           | 72.11           | 60.23           | 47.76           | 40.64           |
| DB3                             | 55.65           | 50.82           | 75.37           | 70.17           | 42.92           | 43.81           |
| DB4                             | 41.05           | 47.49           | 40.59           | 59.05           | 36.09           | 42.72           |

V. CONCLUSION

This paper presented a report on the experimental study of the impact of false minutiae points on the performance of AFIS. A 3-tier algorithm was implemented with the results at each level showing relevance and meaningfulness. Results for fingerprint minutiae extraction algorithm revealed its inability to enforce the extraction of only true minutiae points. At the post-processing stage, only the true minutiae points; namely ridge end and bifurcation were extracted. Analysis of experimental results for both feature extraction and post-processing algorithms on FVC2000, FVC2002 and FVC2004 fingerprint databases revealed that for speedy and reliable performance of AFIS, all forms of false minutiae points must be eliminated from its operation.

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