Fusion Approach for Fingerprint Matching for Improved System Accuracy

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Abstract

In automated fingerprint identification systems, an efficient and accurate alignment algorithm in the preprocessing stage plays a crucial role in the performance of the whole system, affecting greatly the speed and accuracy otherwise.

This paper proposes a fusion scheme (weighted sum) for aligning the enrolled and query images using modified ring model and cross correlation approaches. Both the methods align the pair of fingerprint images based on the single singular point (as a reference point). Matching is then performed using Euclidean distance based matcher. This model is tested on both publicly available (Cross Match Verifier 300 sensor) as well as proprietary (Lumidigm Venus V100 OEM Module sensor) fingerprint databases scanned at 500 dpi. The experiments show that this fusion approach improves the overall system accuracy: FNMR and FMR significantly dropped to 3.23% & 2.67% respectively for Cross Match Dataset and 0% & 1.33% respectively for Lumidigm Dataset. Hence, the combination of these two alignment methods effectively strengthens the performance of the matcher.

Keywords: *Fusion Matcher, Fingerprint Image Alignment, Ring Model, Cross Correlation, Euclidean Distance.*

1. Introduction

Due to rotation, translation and scaling problems between the query (probe) and the enrolled fingerprints from the database, alignment becomes a necessary step in most of the fingerprint recognition systems. Keeping focus primarily on fingerprint image alignment, two different image-based alignment techniques are fused together. The two methods are: modified ring model and cross correlation, they are explained in detail in section 2. Fusion rule and experimental results are discussed in Sections 3 and 4 respectively.

2. Alignment Approaches

In this section, working principles and implementation details of the two alignment approaches are discussed. The two alignment methods are: modified ring model and cross correlation. They are discussed in sub-sections 2.1 and 2.2.

2.1 Modified Ring Model-based Alignment

Original Ring model, as in [1], aligns the fingerprints based on singular points and edge orientation. Singular point serves as a translation reference point and rotation center, and rotation angle is computed from the edge orientation around the singular point. The ring model also figures out how well the two fingerprint images are aligned by computing the angle difference. Based on this, the best alignment is selected out of several alignments.

In this paper, we have modified original ring model to enhance the speed and effectiveness, while keeping the main idea intact, as was proposed in [1]. Firstly, while looking for reference points one in each enrolled and query images, (along and about which, the query image is translated and rotated, so that it can be aligned with the enrolled image), singularity points are detected in both the images using methods discussed in [5][6]. In case of multiple singular points, a bounding box of size 100x100 is drawn around the centroid. The centroid is estimated with respect to the region of interest (ROI) of the image. The bounding box is used with an intention to narrow down the candidate singular points, as shown in Fig. 1. Further, in case of multiple selections, to pin down a single singular point, the singular point with the smallest y coordinate is selected as a reference point.

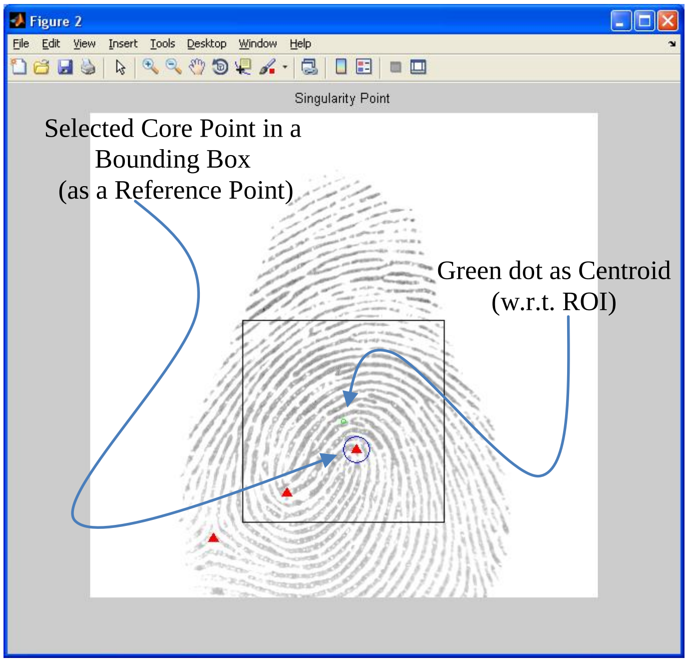


Figure 1. Process to select a single reference point.

Working Principle of the original ring model is as follows: a ring with radius range = (20, 40) is selected [1], as shown in Fig. 2.

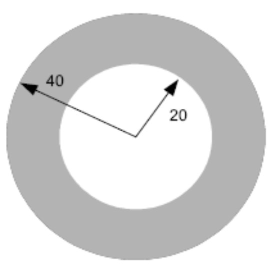


Figure 2. A ring with radius range = (20, 40).

The ring model determines the best rotation angle for the query edge image based on single singular point. According to Fig. 3, the line Li rotates in counter-clock direction at every 5 degrees. To calculate the direction difference between the Li and the intersection points Eij, formula in Eq. (1) is used:

$$A_i = \frac{1}{N}\sum_j \cos(DL_i - DE_{ij}) \qquad (1)$$

The Eq. (1) uses cosine value instead of sine value. This is because around a singular point, the direction difference (DL_i – DE_{ij}) is often near 90°, at which the cosine value changes much faster than the sine value. Hence, the cosine formula is chosen for computing the A value so that it is more sensitive to the small changes in (DL_i – DE_{ij}) than using the sine formula. After the L_i rotates from i=0° to i=355° at 5° per step, the series of A_i values form a histogram [1]. By shifting the input image's histogram every 5°, the histogram difference between the enrolled image and query image (rotated) is computed. The optimal rotation for alignment is the shift that gives the minimum histogram difference. The alignment with the minimum histogram difference is selected as the final alignment.

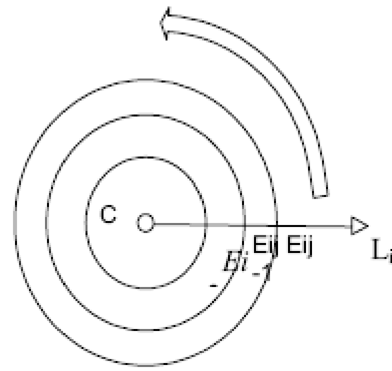


Figure 3. Rings of edges with intersecting line from ring center [1].

Fig. 4 and 5 shows the alignment results of the ring model, where the edge map of the query image is translated and rotated to obtain the best overlapping with the edges of the enrolled image.

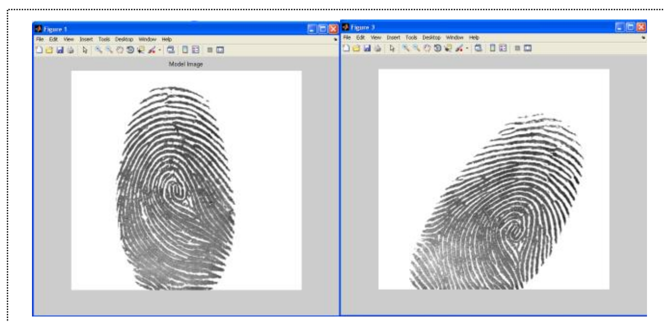


Figure 4. Enrolled (left) and Query (right) Images.

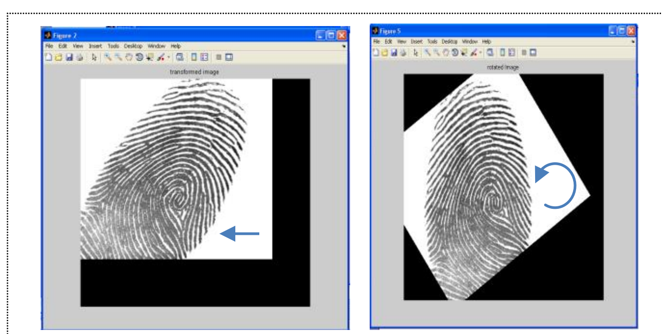


Figure 5. Translated (left) and Rotated (right) Query Image with respect to Enrolled Image as shown in Fig. 4.

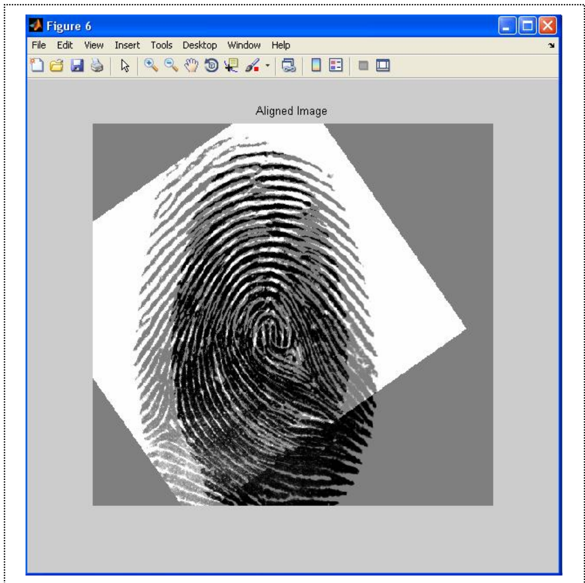


Figure 6. Aligned and overlaid Enrolled and Query Images.

2.2 Cross Correlation-based Alignment

In this method, we achieve the best alignment between the given images in two phases by looking for the points that are maximally correlated with each other by computing correlation between the skeletonized images (enrolled and query, where enrolled images is treated as a reference image and query image as template): i) finding the best alignment by using correlation between the skeletonized images according to the translation, followed by ii) second alignment, wherein, we again use correlation between the skeletons to find the best alignment according to the rotation. Both the phases are shown in Fig. 7.

The implementation closely follows the formula in Eq. (2) and evaluates the normalized cross correlation value γ at each point (u, v) for enrolled image 'f' and the query image (as template) 't', which has been shifted by u steps in the x direction and by v steps in the y direction. Eq. (2) gives a basic definition for the normalized cross correlation coefficient [2][3][4]:

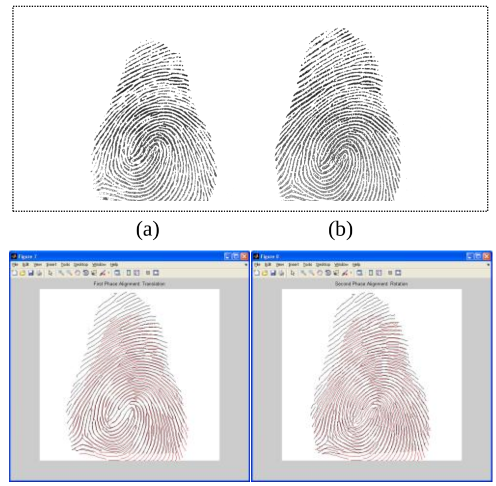
$$\gamma(u,v) = \frac{\sum_{x,y}[f(x,y) - \overline{f}_{u,v}][\overline{t}(x-u,\ y-v) - \overline{t}]}{\sqrt{\sum_{x,y}[f(x,y) - \overline{f}_{u,v}]^2 \sum_{x,y}[\overline{t}(x-u,\ y-v) - \overline{t}]^2}} \quad (2)$$

Where, 'f' is the enrolled (reference) image, 't' is the mean of the query image and '$\overline{f}_{u,v}$' is the mean of $f(x,y)$ in the region under the query image.

In Eq. (2), $\overline{f}_{u,v}$ denotes the mean value of $f(x,y)$ within the area of the query image (template) t shifted to (u,v), which is calculated by:

$$\overline{f}_{u,v} = \frac{1}{N_x N_y} \sum_{x=u}^{u+N_x-1} \sum_{y=v}^{v+N_y-1} f(x,y) \quad (3)$$

'$\overline{t}$' is the mean of the query image 't'. The denominator in Eq. (2) is the variance of the zero mean image function $f(x,y) - \overline{f}_{u,v}$ and the shifted zero mean template (query image) function $\overline{t}(x-u,\ y-v) - \overline{t}$. Due to this normalization, $\gamma(u,v)$ is independent to changes in brightness or contrast of the image, which are related to the mean value and the standard deviation.



(a) (b)

(c) (d)

Figure 7. (a) Enrolled Image, (b) Query Image, (c) Translated Query Image, (d) Rotated Query Image.

3. Fusion Scheme: "Weighted Sum" Rule

The fusion engine combines the individual quality scores, which are the outcomes of the matchers, in principle, working with two different alignment modules. The engine then generates the final matching score used by the recognition system to finally decide whether the two impressions are same or not, as shown in Fig. 8.

The fusion rule adopted here for combining the scores is: the 'Weighted Sum Rule' [7][8]. In weighted sum rule (Ong et al., 2003; Nakagawa et al., 2006), a weighted factor is multiplied with the score and then sum is calculated as given in Eq. (4).

$$f = \sum_{i=1}^{M} W_i x_i \quad (4)$$

Each matcher carries some weight, W_i, such that $\sum_{i=1}^{M} W_i = 1$. The matcher weights are calculated through empirical calculations. In our case, we have assigned 70% weight to modified ring model and 30% to cross correlation.

Same matcher has been used in both the cases, which, in principle, is based on the Euclidean distance [10][11].

4. Experimental Results

Publicly available [12] (Cross Match Verifier 300 sensor) and a proprietary (Lumidigm Venus V100 OEM Module sensor) fingerprint databases (@ 500 dpi) have been chosen as test data to assess the performance of this proposed fusion approach for aligning and matching a pair of fingerprints. The scheme is implemented in MATLAB. The experiments show that this fusion approach significantly improves the overall system accuracy: FNMR and FMR significantly dropped to 3.23% & 2.67% respectively for Cross Match Dataset and 0% & 1.33% respectively for Lumidigm Dataset. Few cases from experimental results in the form of comparison charts are presented in Fig. 13 and 14. The corresponding graphs are shown in Fig. 9, 10, 11 and 12.

5. Conclusions

In this paper, we have proposed a hybrid model for achieving highly accurate alignment of enrolled and query fingerprint images. Experimental results clearly advocate the fact that the two alignment methods in conjunction effectively strengthen the performance of the matcher. Though the fusion scheme could perform extremely well over the small datasets presented here, it needs to be confirmed and tested rigorously over full range of FVC2004 and other publicly available large datasets. This approach is all towards image-based matching techniques.

Acknowledgments

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References

[1] Fang Li, Leung, M.K.H. and Chuan Liu, “Fingerprint alignment using ring model”, Third International Conference on Information Technology and Applications (ICITA), 2005.

[2] Lewis, J. P., "Fast Normalized Cross-Correlation," Vision Interface, Canadian Image Processing and Pattern Recognition Society, Quebec City, Canada, 1995.

[3] Lewis, J. P., "Fast Template Matching”, Vision Interface, Canadian Image Processing and Pattern Recognition Society, Quebec City, Canada, p. 120-123, May 15-19, 1995.

[4] Kai Briechle and Uwe D. Hanebeck, "Template matching using fast normalized cross correlation", Proc. SPIE 4387, 95 (2001).

[5] Asker M. Bazen and Sabih H. Gerez, “Extraction of Singular Points from Directional Fields of Fingerprints”, Mobile Communications in Perspective, Annual CTIT Workshop, Enschede, The Netherlands, University of Twente, Center for Telematics and Information Technology, February 2001.

[6] Krzysztof Kryszczuk and Andrzej Drygajlo, “Singular point detection in fingerprints using quadrant change information”, The 18th International Conference on Pattern Recognition (ICPR'06), 2006.

[7] Tejas Joshi, Somnath Dey and Debasis Samanta, “Multimodal biometrics: state of the art in fusion techniques”, International Journal of Biometrics, Vol. 1, No. 4, pp. 393-417, 2009

[8] Toh, K-A, and Yau, W-Y, “Combination of hyperbolic functions for multimodal biometrics data fusion’, IEEE Trans. On Systems, Man, and Cybernetics, Part B, vol. 34, no. 2, pp. 1196–1209, 2004.

[9] Lin Hong, Yifei Wan, and Anil Jain, “Fingerprint Image Enhancement: Algorithm and Performance Evaluation”, IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 20, No. 8, August 1998.

[10] Calvin R. Maurer, Rensheng Qi, Vijay Raghavan, “A Linear Time Algorithm for Computing Exact Euclidean Distance Transforms of Binary Images in Arbitrary Dimensions”, IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 25, NO. 2, FEBRUARY 2003.

[11] http://en.wikipedia.org/wiki/Euclidean_distance

[12] http://neurotechnology.com/download.html

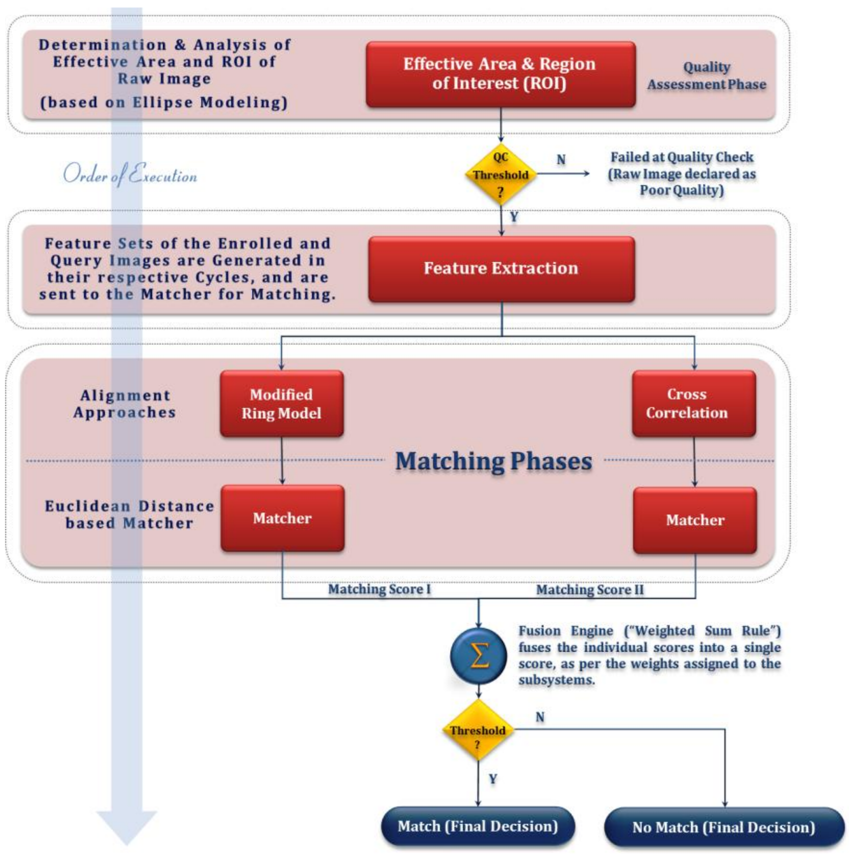

Figure 8. Fusion Approach: Flowchart.

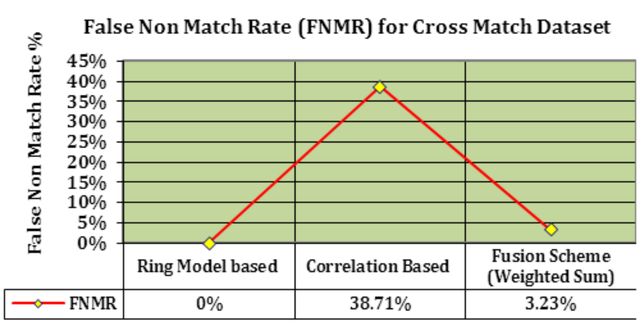

Figure 9. FNMR: Cross Match Dataset.

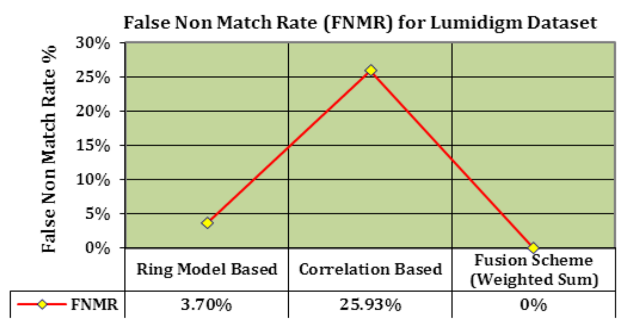

Figure 11. FNMR: Lumidigm Dataset.

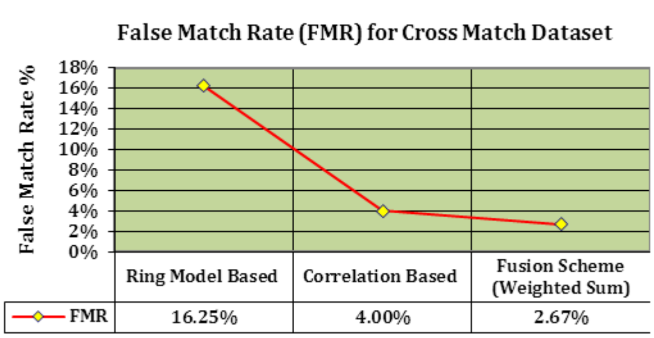

Figure 10. FMR: Cross Match Dataset.

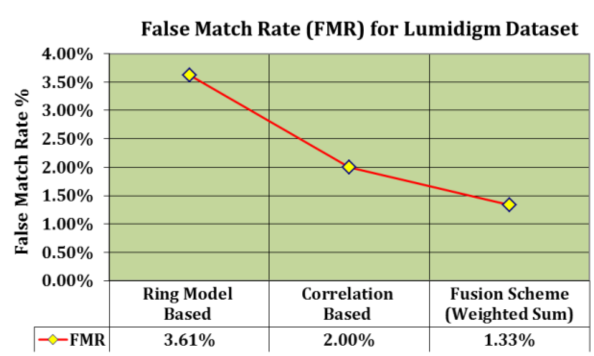

Figure 12. FMR: Lumidigm Dataset.

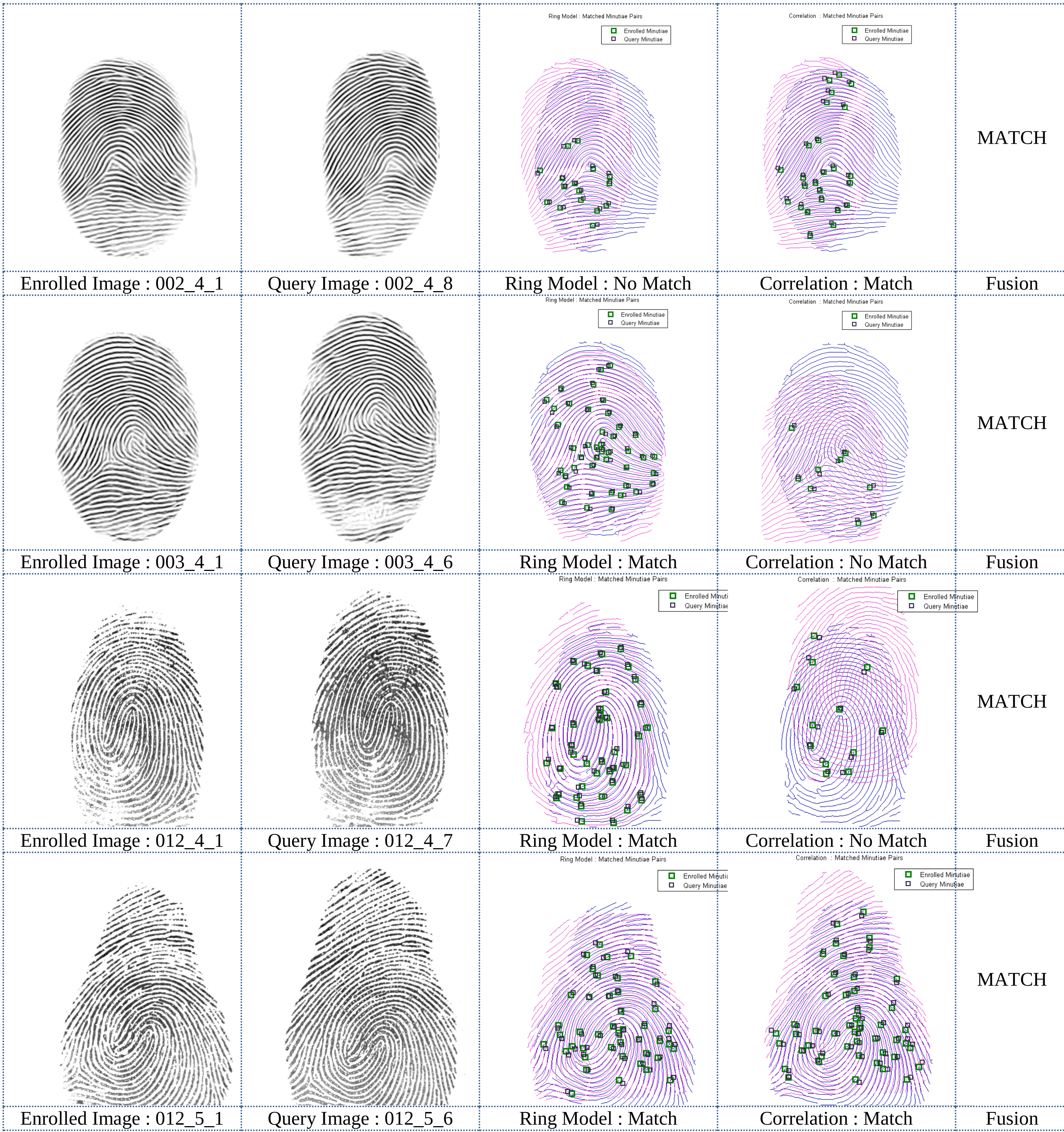

Figure. 13 Experimental Results.

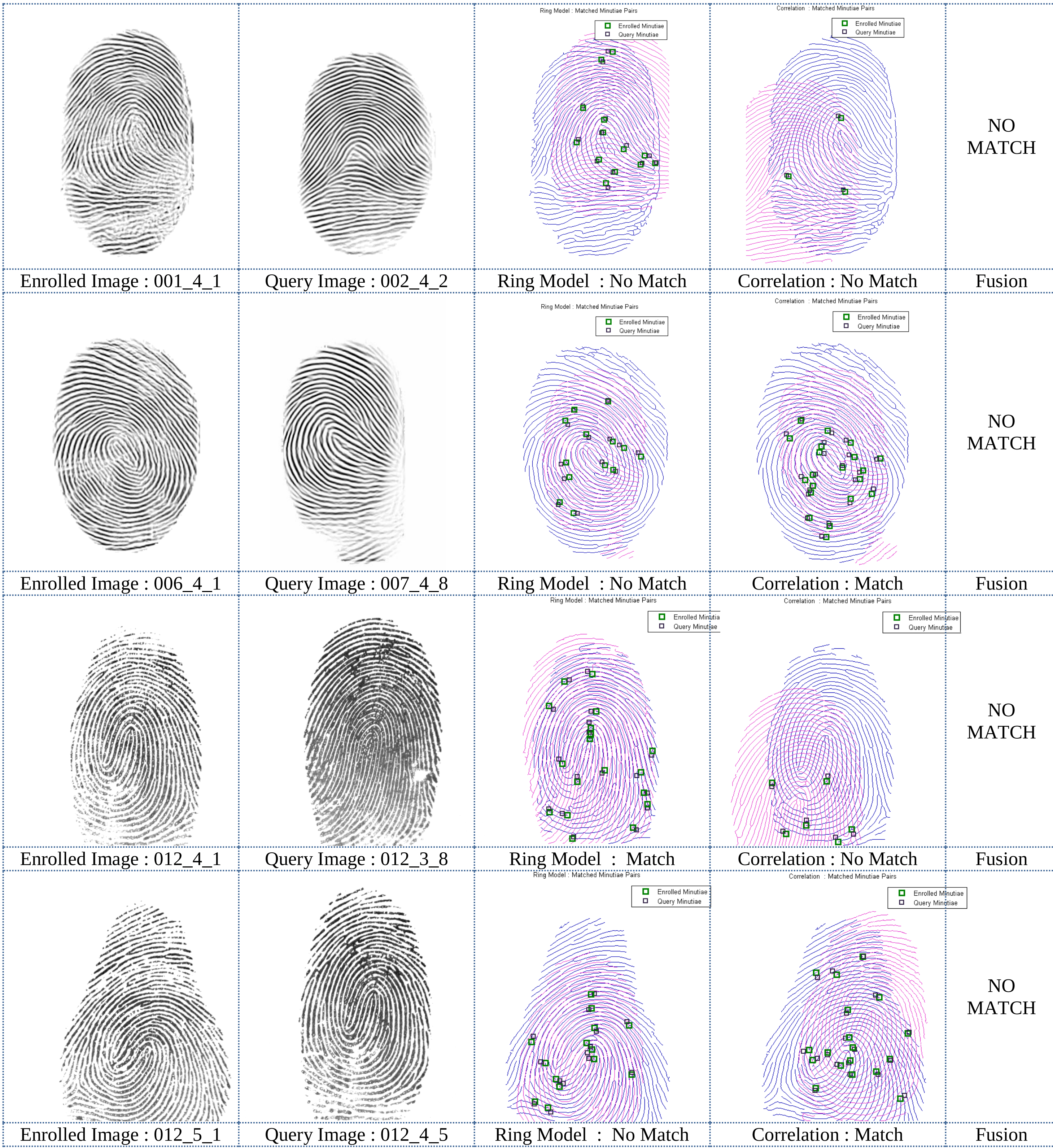

Fig. 14 Experimental Results.