Integrating Rare Minutiae in Generic Fingerprint Matchers for Forensics

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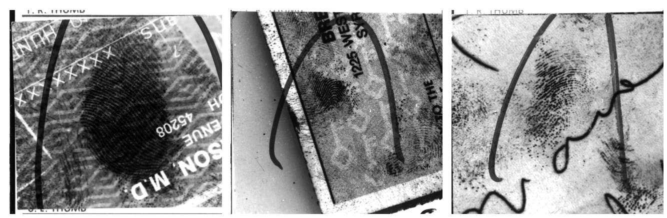
***Abstract*—Automated Fingerprint Identification Systems (AFIS) are commonly used by law enforcement agencies to narrow down the possible suspects from a criminal database. AFIS do not use all discriminatory features available in fingerprints but typically use only some types of features automatically extracted by a feature extraction algorithm. Latent fingerprints obtained from crime scenes are usually partial in nature which results to only very few number of reliable minutiae. Comparing a partial minutiae pattern to a full minutiae pattern is a difficult problem. Towards solving this challenge, we propose a method that exploits extended fingerprint features (unusual/rare minutiae) not commonly considered in typical minutiae-based matchers. The method we propose in this work can be combined with any existing minutiae-based matcher. We first compute a quantitative measure based on least squares between latent and tenprint minutiae points, with rare minutia feature as reference point. Then the similarity score of the reference minutiae-based matcher is modified based on the least square quantitative measure. The modified similarity score thus obtained incorporates the contribution of rare minutia features. We use a realistic forensic fingerprint casework database in our experiments which contains rare minutia features obtained from Guardia Civil, the Spanish law enforcement agency. Experiments are conducted using two reference minutiae-based matchers, namely: NIST-Bozorth3 and VeriFinger. We report a significant improvement in the rank identification accuracies when the reference minutiae matchers are augmented with our proposed algorithm based on rare minutia features.**

I. Introduction

A common forensic evidence used in criminal investigations is latent fingerprint, but identifying the suspects based on latent fingerprints is not an easy task. This is mainly attributed to the poor quality of the latent fingerprints obtained from the crime scenes. When a latent fingerprint is found, the criminal investigators first search for the suspect in criminal database using an Automated Fingerprint Identification System (AFIS) to narrow down their manual work. If there is a match, then the individual is linked to the crime under investigation. Individualization (*identification or match*) is the decision yielded by a forensic examiner about the latent fingerprint belonging to a particular individual. This is the outcome of the Analysis, Comparison, Evaluation and Verification (ACE-V) [1] methodology currently followed in friction ridge examination.



(a) Good (b) Bad (c) Ugly

Fig. 1. Subjective quality classification of latent fingerprint images in NIST Special Database 27 (NIST-SD27).

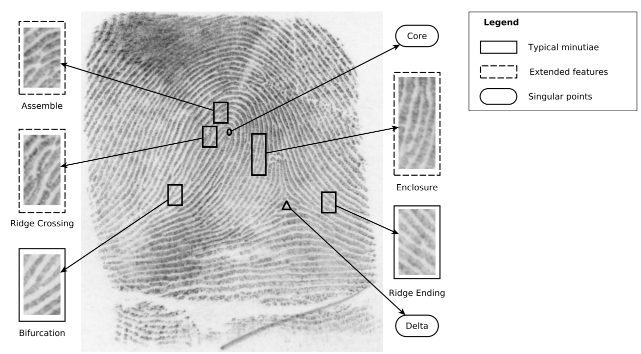


Fig. 2. Typical minutiae (ridge-ending, bifurcation), extended features (assemble, ridge-crossing, enclosure) and singular points (core, delta) in an exemplar fingerprint from NIST-SD27 database.

In general, latent fingerprints are partial in nature and are of varying quality (see Figure 1), mostly distorted, smudgy, blurred etc. These factors lead to high number of unreliable features extracted in fully automatic mode, and make it difficult for AFIS to perform well. AFIS do not use all the discriminatory features that could be derived from a fingerprint, mainly due to the limitations of automatic and reliable extraction of all types of discriminatory features. The accuracy of feature extraction and matching algorithms for AFIS in forensic scenario is of great importance to avoid erroneous individualization.

Current practice in latent AFIS technology involves marking the latent fingerprint features manually by forensic examiners and then using both the latent fingerprint image and the manually marked features to search in the AFIS for a list of possible suspects. To avoid this burden of manual marking and with the hope of fully automating the latent AFIS, NIST conducted a public evaluation of commercial AFIS performance in Lights-Out mode, where the feature extract and matching are completely automatic. This was a multi-phase open project called Evaluation of Latent Fingerprint Technologies (ELFT) [2]. In the final evaluation of ELFT, the best performing system achieved only 63.4% Rank-1 identification accuracy. In [3], it is concluded that only a limited class of latents which are of good quality benefits from automated procedures, and still manual intervention is necessary. The procedures of marking the minutiae, determining the subjective quality of latents, etc. still need to be carried out manually.

Any features that are not currently used by commercial AFIS are generally termed as Extended Feature Sets (EFS) [4]. To use EFS in automated systems, reliable feature extraction algorithms are mandatory. For testing the feasibility to include EFS in latent AFIS, NIST conducted another multi-phase commercial latent AFIS evaluation called Evaluation of Latent Fingerprint Technologies - Extended Feature Sets (ELFT-EFS) [5].

ELFT-EFS was conducted in a "Semi Lights-Out" mode which involves manual intervention as compared to the "Lights-Out" mode for ELFT which was fully automatic. The main purpose of ELFT-EFS was to determine the effectiveness of forensic examiner marked latent fingerprint features on the latent identification accuracy. NIST conducted two evaluations for ELFT-EFS. In [6], it is reported that though the highest measured rank identification accuracy achieved by an individual matcher at Rank-1 was 71.4%, approximately 82% of the latents were correctly matched at Rank-1 when more matchers were combined. This corroborates the potential for additional accuracy improvement when combining multiple algorithms [7].

In this work, we propose a method to improve the identification accuracy of minutiae-based matchers for partial latent fingerprints by incorporating reliably extracted rare minutia features. Most minutiae-based fingerprint matchers use only two prominent ridge characteristics namely *ridge-endings* and *bifurcations*.

We propose an algorithm that will modify the similarity scores of minutiae-based matchers based on the presence of rare minutia features like *assemble*, *ridge crossing*, *enclosures*, *dots*, *interruptions, etc* (see Figure 2). The weights that we use to modify the similarity scores are obtained based on the probability of occurrence of such rare minutia features. The decision for a match or non-match is automatically estimated based on least squares fitting of an affine transformation between the latent minutiae set and the tenprint minutiae set. We show a significant improvement in the overall rank identification accuracies for two minutiae-based matchers (NIST-Bozorth3 and VeriFinger) when their similarity scores are modified using our proposed algorithm which incorporates rare minutia features.

The main contributions of this work are as follows:

1) A methodology to adapt any minutiae-based matcher by incorporating information from rare features.
2) Experimental demonstration of the performance improvement of minutiae-based matchers when incorporating information from rare features.
3) We finally present also various population statistics about rare minutia features present in a realistic forensic casework database obtained from Spanish law enforcement agency (Guardia Civil).

In the following sections, we review related works about the use of EFS and other pre-processing to improve AFIS performance, and describe: the database and statistics of rare minutia features, the proposed algorithm to modify the similarity scores based on rare features, experiments, results and conclusions.

II. Related works

A detailed study on extended fingerprint feature sets was reported by Jain [8]. This includes several extended features from Level-One, Level-Two and Level-Three. It was concluded in [8] that manual intervention is strongly recommended while using EFS, as well as extended features from Level-One and Level-Two are highly recommended to be incorporated in latent AFIS. Extended features such as ridge flow map, ridge wavelength map, ridge quality map, and ridge skeleton have shown significant improvements in latent identification accuracies. Level-One and Level-Two details used in [8] [9] are insensitive to image quality, and do not rely on high resolution images. To incorporate Level-Three EFS such as pores, dots, incipients, etc, it is essential to have high resolution fingerprint images.

The use of pores as extended features was studied in high resolution 1000 ppi images by Zhao et al. [4] and Jain et al. [10]. Dots and incipients were studied by Chen et al. [11]. Among pores, dots and incipients, pores resulted in better performance [4]. Even though high resolution 1000 ppi images were used, live scan images resulted in easy detection of pores automatically, which was not the case with inked fingerprint images. Pore extraction based on skeletonized and binary images was studied by Stosz et al. [12] [13] and Kryszczuk et al. [14]. These techniques were demonstrated effective only on very good quality high resolution fingerprint images scanned approximately at 2000 ppi [12]. These methods were more sensitive to noise, and the performance degrades for poor quality of fingerprint images and low resolution images.

Score level fusion of different algorithms using various extended fingerprint features was report by Fierrez et al. [15]. Features like singular points, ridge skeleton, ridge counts, ridge flow map, ridge wavelength map, texture measures were studied by analyzing the correlation between them using feature subset-selection techniques. Combination of features show significant improvement in the performance of the system.

When only partial fingerprints are available, pre-alignment of partial minutiae set and full minutiae set based on orientation fields of respective fingerprints helps in reducing

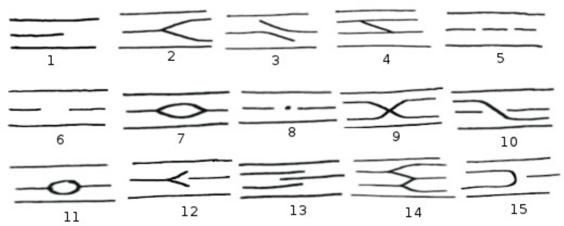


Fig. 3. Minutia types used by Guardia Civil. Names corresponding to individual minutia type numbers can be found in Table I.

No	Minutiae type	No	Minutiae type	No	Minutiae type
1	Ridge Ending	6	Interruption	11	Circle
2	Bifurcation	7	Enclosure	12	Delta
3	Deviation	8	Point	13	Assemble
4	Bridge	9	Ridge Crossing	14	M-structure
5	Fragment	10	Transversal	15	Return

TABLE I
LIST OF MINUTIA TYPES USED BY GUARDIA CIVIL. NUMBERING WITH RESPECT TO FIGURE 3.

No	Minutiae Type	Probability (p_i)	Weight ($w_i = -\log_{10} p_i$)
1	Ridge-ending	0.5634	0.2492
2	Bifurcation	0.3620	0.4413
3	Deviation	0.0015	2.8294
4	Bridge	0.0024	2.6253
5	Fragment	0.0444	1.3523
6	Interruption	0.0021	2.6833
7	Enclosure	0.0204	1.6896
8	Point	0.0036	2.4492
10	Transversal	0.0003	3.5284

TABLE II
THE PROBABILITY OF OCCURRENCE AND THE ENTROPY BASED WEIGHTS FOR THE MINUTIA TYPES PRESENT IN THE 268 LATENT FINGERPRINTS OF GCDB. THE NUMBERS CORRESPOND TO MINUTIA TYPES IN FIGURE 3

the minutiae search space of full fingerprint relative to the size of partial fingerprint. Such reduction in the size of minutiae search space improving the performance of system was reported by Krish et al. [16] [17] [18]. This approach has shown significant improvement in the system performance especially for poor quality latent fingerprints.

III. Database and statistics

The database used in this work was obtained from Guardia Civil, the Spanish law enforcement agency. The Guardia Civil database (GCDB) is a realistic forensic fingerprint casework database, but they are not publicly available. Apart from having typical minutia feature types (*ridge-endings, bifurcations*), GCDB also comprises rare minutia types like *fragments*, *enclosures*, *dots*, *interruptions, etc* [19]. A comprehensive list of rare minutia features used by Guardia Civil are shown in Figure 3 and the corresponding minutiae type names are listed in Table I.

GCDB consists of 268 latent and tenprint (exemplar) pairs of fingerprint images and minutia sets. All the minutiae in the latent fingerprint images were manually extracted by forensic examiners of Guardia Civil. The corresponding mated minutiae in the tenprints were also manually established. This includes the typical (ridge-endings and bifurcations) minutiae and the rare minutiae. These are called *matched* minutiae set, i.e, the minutiae sets for which a one-to-one correspondence is established between the latent and the mated tenprint. The number of minutiae in the latent and its corresponding mated tenprint are the same in case of *matched* minutiae set.

The *ideal* minutiae set (i.e., all possible minutiae) for the tenprints were extracted using VeriFinger SDK [20]. VeriFinger extracts only the typical minutia features from the fingerprint image. We then added the manually extracted rare minutiae into the GCDB tenprint minutiae set. In ideal minutiae set, the number of minutiae between the latent and the corresponding mated tenprint minutiae set are not equal. The average number of minutiae in the latents was 13 and that of tenprints was 125.

The original latent minutia sets and the ideal tenprint minutia sets are used in our experiment. To represent some rare minutiae, multiple points were needed. For example, to represent a *deviation*, two points are needed (see type 3 in Figure 3), and to represent an *assemble*, three points are needed (see type 13 in Figure 3). Whenever multiple points are needed to represent a rare minutia, we mapped them to a single point representation by taking the average of locations and orientations of all points representing the rare minutia.

From the 268 latent fingerprint minutia sets, we estimated the probability of occurrence (p_i) of various minutia types. The probability (p_i) and the entropy-based weights ($w_i = -\log_{10} p_i$) for each minutia type present in GCDB are listed in Table II. In the 268 latent fingerprints of GCDB, we noticed only seven types of rare minutia features. They are listed in Table II. Other rare minutia types are not found in the current database used in this study.

IV. Algorithm

The latent fingerprints of GCDB are highly partial in nature, with an average of 13 minutiae per latent. To make an appropriate alignment between the latent minutia points and the tenprint minutia points (with an average of 125 minutia points) requires a reliable reference point. We choose the rare minutia features as reference points to perform the alignment.

Let L and M be the representation of latent and tenprint minutia sets respectively. Each minutia is represented as a quadruple $m = \{x, y, \theta, t\}$ that indicates the (x, y) location as coordinates, the minutia angle θ, and the minutia type t:

$$L = [m_1 \ m_2 \ ... \ m_p], \quad m_i = [x_i \ y_i \ \theta_i \ t_i]^T, \quad i = 1...p$$

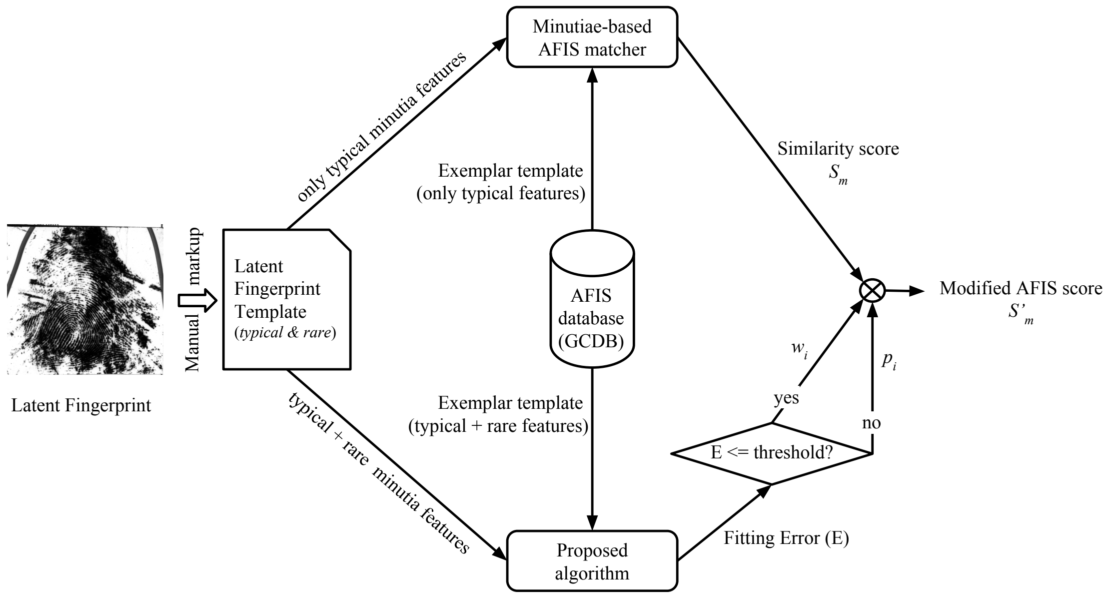


Fig. 4. Sequence of steps in estimating the modified similarity score of a reference minutiae-based matcher.

$$M = [m'_1 \; m'_2 \; ... \; m'_q], \quad m'_j = [x'_j \; y'_j \; \theta'_j \; t'_j]^T, \quad j = 1...q,$$

where p and q are the number of minutiae in L and M respectively. If $t > 2$, then the minutia is of rare type (from Table I), and $[\,\cdot\,]^T$ denotes transpose.

The algorithm to generate modified similarity score of a minutiae matcher is described in two stages. Similarity scores of minutiae matcher is modified only if they contain rare minutia features.

The first stage of the algorithm estimates the least square fitting error for an affine transformation of the latent minutiae set onto a tenprint minutiae set. The second stage of the algorithm modifies the similarity score generated by the minutiae-based matcher based on the fitting error. Other works related with modifying the similarity score based on pre-alignment are reported in [16], [21], [22]. The sequence of steps involved in generating the modified score of the minutiae matcher using our proposed algorithm is summarized in Figure 4.

Stage-1 : Least Square Fitting Error

Step 1: To find the affine transformation between L and M, it is first needed to establish a one-to-one correspondence between minutiae from L and minutiae from M. Let the subset of minutiae from M which establishes correspondence with minutiae from L be denoted as M_s.

Step 2: Superimpose one rare minutia point of L onto the corresponding rare minutia point of M, only if they both are of the same type (if there are multiple rare minutia points, take any). If the type of the rare minutia between L and M differs, or M does not contain any rare minutiae, then the comparison is assumed to be non-match.

Step 3: To establish the correspondence between latent and tenprint minutia points, we choose the minutia points from M that are close to the minutia points of L. The Euclidean distance is calculated between the minutia pairs (only typical minutiae) to determine whether the pairs are close or not.

Step 4: To compensate for rotation alignment, we rotate the latent in the range $[-45°, +45°]$ with respect to the superimposed rare minutiae, and estimate the Euclidean distance for each rotation step of size $1°$.

Step 5: The optimal rotation is the one for which the average sum of distances between closest pairs is minimum.

Step 6: After the alignment, all those minutia pairs which are within a threshold distance are considered to be mated pairs, and a one-to-one correspondence is established between them. As a result, we obtain a subset M_s of the tenprint minutiae M. After establishing the correspondence, the number of minutiae between L and M_s are the same.

Step 7: Once the correspondence is established, we find the least square fitting error for the affine transformation between the latent minutia points and the subset of tenprint minutiae set. For $\hat{L}$ and $\hat{M}_s$, which are the modified version of L and M_s with only the (x, y) locations as minutia representation augmented with a value 1, i.e,:

$$\hat{L} = [\hat{m}_1 \; \hat{m}_2 \; ... \; \hat{m}_p]; \quad \hat{m}_i = [x_i \; y_i \; 1]^T; \quad i = 1...p$$
$$\hat{M}_s = [\hat{m}'_1 \; \hat{m}'_2 \; ... \; \hat{m}'_p]; \quad \hat{m}'_j = [x'_j \; y'_j \; 1]^T; \quad j = 1...p,$$

we are looking for some affine transformation matrix

$$A = [a_{jk}]_{j,k=1...3} \tag{1}$$

and some translation vector

$$\tau = [\tau_1 \; \tau_2 \; ... \; \tau_p]; \quad \tau_1 = \tau_2 = ... = \tau_p = [\delta_x \; \delta_y \; 1]^T; \tag{2}$$

such that

$$\hat{M}_s \approx A\hat{L} + \tau \tag{3}$$

where $[\delta_x \ \delta_y]$ is the translation needed to superimpose the rare minutia of L and M.

Step 8: Find the least square fitting error between $\hat{L}$ and $\hat{M}_s$ defined as follows:

$$E^{\hat{L},\hat{M}_s} = \frac{1}{p}\sum_{i=1}^{p} ||\hat{m'_i} - A\hat{m}_i - \tau_i||_2^2 \tag{4}$$

where $||\hat{m'_i} - A\hat{m}_i - \tau_i||_2$ is the L_2 norm.

For a match comparison, we expect this fitting error to be small, whereas for a non-match comparison, the fitting error is expected to be large.

If there are multiple matching rare minutiae feature between L and M_s, then $E^{\hat{L},\hat{M}_s}$ is calculated for all such minutiae types. The fitting error for such a comparison is chosen to be the minimum of all the fitting errors calculated.

Stage-2 : Weighted scores

Step 9: Using a standard minutia matcher, generate the similarity score S_m between L and M. The modified similarity score S'_m based on a fitting error threshold E is obtained as follows:

$$S'_m = \begin{cases} S_m \times w_i & \text{if } E^{\hat{L},\hat{M}_s} \leq E, \\ S_m \times p_i & \text{otherwise} \end{cases} \tag{5}$$

where w_i is the derived entropy based weight, and p_i is the probability of occurrence of a particular rare minutia type t_i based on which fitting error is estimated. The values for w_i and p_i for all minutiae type t_i are listed in Table II. If $E^{\hat{L},\hat{M}_s} \leq E$, then the comparison is deemed to be a match, and if $E^{\hat{L},\hat{M}_s} > E$, the comparison is deemed to be a non-match.

Thus, we obtain a modified similarity scores S'_m for a particular minutiae matcher by rewarding or penalizing the similarity scores based on the fitting error obtained using our approach.

V. Experiment

We performed all our experiments on the minutia sets of 268 latents and corresponding 268 tenprints of GCDB. To generate similarity scores, we used two minutiae matchers namely: NIST-Bozorth3 [23] and VeriFinger SDK [20]. When reporting the rank identification accuracies in our experiments, there are 268 match comparisons and 268×267 non-match comparisons. NIST-Bozorth3 is a minutiae based fingerprint matcher that is specially developed to deal with latent fingerprints and is publicly available. This matcher is part of the NIST Biometric Image Software (NBIS) [23], developed by NIST. VeriFinger is a commercial SDK that is widely used in academic research. We report the performance accuracy and improvement of all the matchers using Cumulative Match Characteristic (CMC) curves.

A. Experiment: Importance of rare minutiae

Two configurations are compared in this experiment to demonstrate the importance of rare minutia features:

1) *Typical Features*: Only the typical minutia features (ridge-endings and bifurcations) were used to generate similarity scores using the reference minutiae-based matchers.
2) *Typical + Rare Features*: The similarity scores generated by the reference minutiae-based matchers are modified using our proposed algorithm.

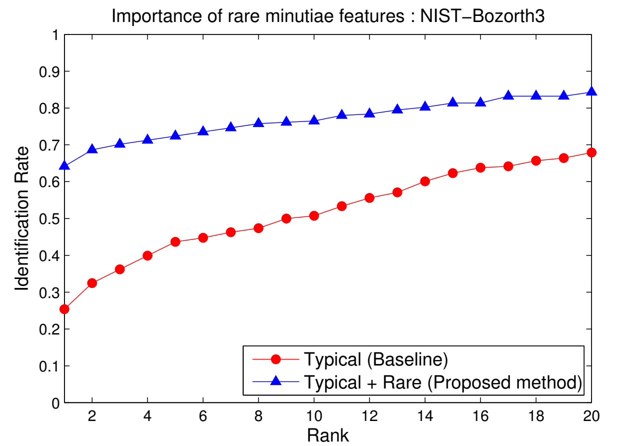


Fig. 5. Improvement in rank identification when incorporating rare minutia features for NIST-Bozorth3.

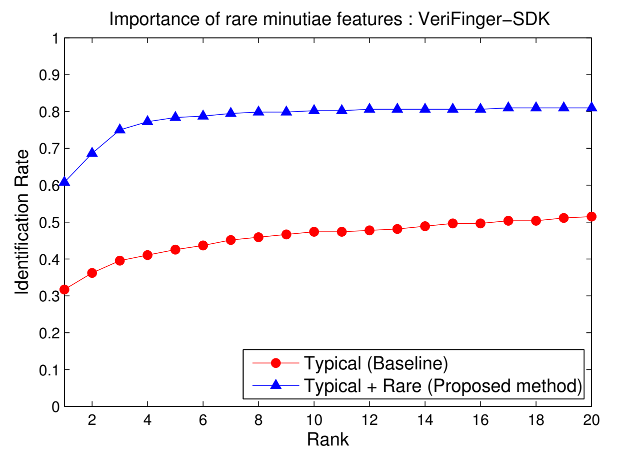


Fig. 6. Improvement in rank identification when incorporating rare minutia features for VeriFinger-SDK.

For a given comparison, the similarity scores generated by the minutiae-based matcher are modified based on fitting error alone. If the fitting error was less than or equal to E, then the comparison is deemed to be a match comparison and their similarity score is rewarded as indicated in Eq.(5). If the fitting error is more than E (a non-match comparison), then the similarity score is penalized. The value of E was empirically chosen as 4 in this experiment. If no rare minutiae is present, then the similarity score of reference matcher is not modified.

Figures 5 and 6 show the rank identification accuracy in CMC curve for both NIST-Bozorth3 and VeriFinger. For NIST-Bozorth3, the Rank-1 identification improved from 25.37% to 64.18%, and for VeriFinger, the Rank-1 identification improved from 31.72% to 60.82% when rare minutia features were incorporated and the similarity scores are modified based

Matcher	Typical Features (Rank-1) in %	Typical + Rare (Rank-1) in %
NIST-Bozorth3	25.37	64.18
VeriFinger	31.72	60.82

TABLE III
RANK-1 IDENTIFICATION FOR NIST-BOZORTH3 AND VERIFINGER UNDER VARIOUS CATEGORIES OF ANALYSIS.

on the fitting error proposed in our algorithm. Moreover, overall there is a consistent and significant improvement in rank identification accuracies for both reference minutiae-based matchers when we incorporate our proposed algorithm. The average number of minutiae per latent is only 13, and among them, only 92% of minutiae are typical (see Table II). This implies a further reduction in typical minutiae counts per latent. Since the typical minutiae count per later is very less, the performance of the minutiae-based matchers are low when only typical minutiae are used. Table III summarizes the Rank-1 accuracy for both NIST-Bozorth3 and VeriFinger under the two configurations considered.

VI. CONCLUSIONS

One of the crucial challenges faced by AFIS is on how to improve the rank identification accuracies when only partial fingerprints are available. We proposed a methodology that makes use of reliably extracted rare minutia features to improve the rank identification accuracies for minutiae matchers.

The usefulness of the proposed method is demonstrated on two widely used minutiae-based matchers, NIST-Bozorth3 and VeriFinger. Both matchers showed significant improvements in the rank identification accuracies when their similarity scores were modified based on the fitting error proposed in our methodology.

We conclude that even if we have only few number of minutiae in a partial latent, presence of reliably extracted rare minutia features makes the comparison more robust. In our experiments, we used the rare minutia features that were manually extracted by forensic examiners. The results in this work inform the future minutiae extraction algorithms to incorporate robust automatic extraction of rare minutia features from high resolution fingerprint images. This will significantly improve the current state of the art in AFIS adapted for latent fingerprints.

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REFERENCES

[1] D. R. Ashbaugh, "Quantitative-qualitative friction ridge analysis: an introduction to basic and advanced ridgeology," *Boca Raton: CRC press*, 1999.

[2] NIST-ELFT, 2013. Evaluation of latent fingerprint technologies.

[3] M. Indovina, R. Hicklin, and *et al.*, "NIST evaluation of latent fingerprint technologies: Extended feature sets [Evaluation #1]," *NIST Interagency/Internal Report (NISTIR) - 7775, Tech. Rep.*, 2011.

[4] Q. Zhao and A. Jain, "On the utility of extended fingerprint features: A study on pores," *IEEE Computer Society Conference In Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 9–16, 2010.

[5] M. Indovina, R. A. Hicklin, and G. I. Kiebuzinski, "ELFT-EFS Evaluation of Latent Fingerprint Technologies: Extended Feature Sets [Evaluation# 1]," *National Institute of Standards and Technology, US Department of Commerce NISTIR 7775*, 2011.

[6] M. Indovina, V. Dvornychenko, R. A. Hicklin, and I. G. Kiebuzinski, "ELFT-EFS Evaluation of Latent Fingerprint Technologies: Extended Feature Sets [Evaluation# 2]," *National Institute of Standards and Technology, US Department of Commerce NISTIR 7859*, 2012.

[7] J. Fierrez-Aguilar, Y. Chen, J. Ortega-Garcia, and A. K. Jain, "Incorporating image quality in multi-algorithm fingerprint verification," in *Proc. IAPR Intl. Conf. on Biometrics, ICB*, vol. 3832 of *LNCS*, pp. 213–220, Springer, January 2006.

[8] A. Jain, "Automatic Fingerprint Matching Using Extended Feature Set," *US Department of Justice, Document NNCJ, 235577*, 2010.

[9] A. Jain and J. Feng, "Latent Fingerprint Matching," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 1, pp. 88–100, 2011.

[10] A. Jain, Y. Chen, and M. Demirkus, "Pores and ridges: High-resolution fingerprint matching using level 3 features," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 1, pp. 15–27, 2007.

[11] Y. Chen and A. Jain, "Dots and incipients: extended features for partial fingerprint matching," 2007.

[12] J. D. Stosz and L. A. Alyea, "Automated System for Fingerprint Authentication Using Pores and Ridge Structure," *In Proc. SPIE Conference on Automatic Systems for the Identification and Inspection of Humans*, vol. 2277, pp. 210–223, 1994.

[13] A. R. Roddy and J. D. Stosz, "Fingerprint features-statistical analysis and system performance estimates," *Proceedings of the IEEE*, vol. 85, no. 9, pp. 1390–1421, 1997.

[14] K. Kryszczuk, A. Drygajlo, and P. Morier, "Extraction of Level 2 and Level 3 Features for Fragmentary Fingerprints," *In Proc. COST Action 275 Workshop*, pp. 83–88, 2004.

[15] J. Fierrez, L. Nanni, J. Ortega-Garcia, C. R., and D. Maltoni, "Combining multiple matchers for fingerprint verification: a case study in FVC2000," *Proc. 13th IAPR Intl. Conf. on Image Analysis and Processing, ICIAP, Springer LNCS-3617*, pp. 035–1042, 2005.

[16] R. P. Krish., J. Fierrez, D. Ramos, J. Ortega-Garcia, and J. Bigun, "Pre-registration of latent fingerprints based on orientation field," *IET Biometrics*, pp. 1–11, January 2015.

[17] R. P. Krish, J. Fierrez, D. Ramos, J. Ortega-Garcia, and J. Bigun, "Pre-Registration for Improved Latent Fingerprint Identification," *Proc. IAPR/IEEE 22nd International Conference on Pattern Recognition, ICPR*, pp. 696–701, 2014.

[18] R. P. Krish, J. Fierrez, D. Ramos, J. Ortega-Garcia, and J. Bigun, "Partial Fingerprint Registration for Forensics using Minutiae-Generated Orientation Fields," *IEEE 2nd International Workshop on Biometrics and Forensics, Valletta, Malta*, 2014.

[19] F. Santamaria, "A New Method of Evaluating Ridge Characteristics," *Fingerprint and Identification Magazine*, 1955.

[20] Neurotec-Biometric-4.3, "Neurotechnology VeriFinger-SDK."

[21] A. A. Paulino, J. Feng, and A. K. Jain, "Latent fingerprint matching using descriptor-based hough transform," *IEEE Transactions on Information Forensics and Security*, vol. 8, no. 1, pp. 31–45, 2013.

[22] F. Zheng and C. Yang, "Latent Fingerprint Match using Minutia Spherical Coordinate Code," 8^{th} *IAPR International Conference on Biometrics*, 2015.

[23] NIST-NBIS, "NIST Biometric Image Software," NBIS-Release v4.2.0.