On Matching Latent to Latent Fingerprints

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Abstract

This research presents a forensics application of matching two latent fingerprints. In crime scene settings, it is often required to match multiple latent fingerprints. Unlike matching latent with inked or live fingerprints, this research problem is very challenging and requires proper analysis and attention. The contribution of this paper is three fold: (i) a comparative analysis of existing algorithms is presented for this application, (ii) fusion and context switching frameworks are presented to improve the identification performance, and (iii) a multi-latent fingerprint database is prepared. The experiments highlight the need for improved feature extraction and processing methods and exhibit large scope of improvement in this important research problem.

1. Introduction

Fingerprints can be classified, based on the type of capture as: (i) rolled fingerprint (nail-to-nail), (ii) slap fingerprint and (iii) latent fingerprint [5, 12]. Both rolled and slap fingerprints can be captured by live-scan fingerprint scanners (optical, capacitive scanners etc.) or offline fingerprint capture techniques (inked fingerprints). Over the years, extensive research has been done in matching rolled and slap fingerprints with each other. On the other hand, latent fingerprint recognition is a major research challenge, specially in forensic applications. As shown in Figure 1, latent fingerprint is a special type of fingerprint that is lifted from the surface using chemical processes [12]. They are important evidence and useful for identifying criminals. However, it is difficult to process them due to following challenges or covariates:

- poor quality of latent impression in terms of non-availability of friction ridge information
- partial presence of the fingerprint
- presence of background noise due to the chemical process that is used for lifting the fingerprint and
- non linear distortion in fingerprint ridge patterns.

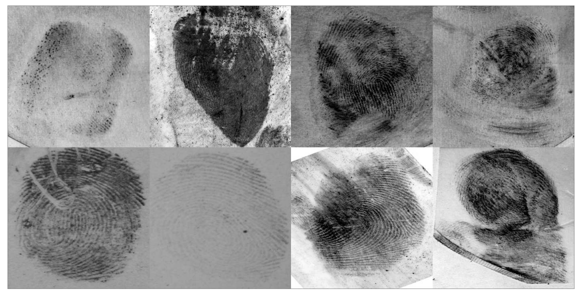


Figure 1: Sample latent fingerprint images.

1.1. Literature Review

Latent fingerprint identification initially started with an expert manually marking and matching the fingerprint impressions. Moses [13] suggested that latent impressions can be matched using Automatic Fingerprint Identification System (AFIS). Jain *et al*. [10] proposed an algorithm to match latent fingerprint images with full fingerprint images. The fingerprints were manually segmented and minutiae and ridge flow were labeled. Matching was performed using the ridge flow and minutiae ground truth provided by the experts. On using the ground truth minutiae for full fingerprints, they reported 98% retrieval at rank 25. Jain *et al*. [9] designed another algorithm for matching latent fingerprints with rolled fingerprints. The orientation field and fingerprint quality were considered to improve the performance accuracy. They reported a rank-20 accuracy of 93.4% in retrieving 258 latent fingerprints from a database of 2258 rolled fingerprints. Feng *et al*. [6], proposed a multi stage filtering technique on large scale fingerprint database to reduce the search space and hence the computation time. They used ridge pattern, singular points, and orientation field for pruning the search space. On matching 258 latent fingerprints with a database of $10,258$ rolled fingerprints, they reported a three fold increase in matching speed and also the rank-1 accuracy increased from 70.9% to 73.3%. In 2010, Yoon *et al*. [19], proposed the latent fingerprint enhancement algorithm. On the manually selected region of interest (ROI) and core point, the proposed algorithm fits

Figure 2: Example illustrating the case when latent fingerprints of same individual are lifted from two different surfaces.

the orientation model to a coarse orientation field obtained by commercial SDK. The enhancement algorithm clearly improved the matching accuracy of the latent fingerprint matching system. Jain and Feng [8] used minutiae, singularity, ridge quality map, ridge flow map, ridge wavelength map, and skeleton for matching latent fingerprint with rolled gallery fingerprint images. Recently, Zhao *et al.* in [20], used level 3 features from 1000ppi image in matching latent fingerprints. Another paradigm in latent fingerprint matching that is being researched upon is the problem of simultaneous latent fingerprint impressions [17]. The simultaneity in latent fingerprints poses interesting questions about the robustness of the existing algorithms.

1.2. Research Contribution

Existing literature on latent fingerprint primarily focuses on matching latent fingerprint with rolled and slap fingerprint images. This research explores an interesting application when both gallery and probe are latent fingerprints. Figure 2 shows two latent impressions of the same individual; such impressions can be obtained from two different crime scenes or different surfaces at the same crime scene. The forensic scientists would like to match the two latent impressions for recognition. Therefore, matching latent fingerprint with a set of other latent fingerprints is a unique problem and less explored in the literature. The key contributions of this paper are summarized below:

- The paper studies the performance of existing minutiae based and ridge flow based algorithms on matching latent to latent fingerprints.
- As shown in Figure 3, different fusion schemes and Support Vector Machine (SVM) based context switching approaches are proposed to combine responses of different algorithms
- A new latent fingerprint database, *IIIT-D Latent database*[1], is prepared.

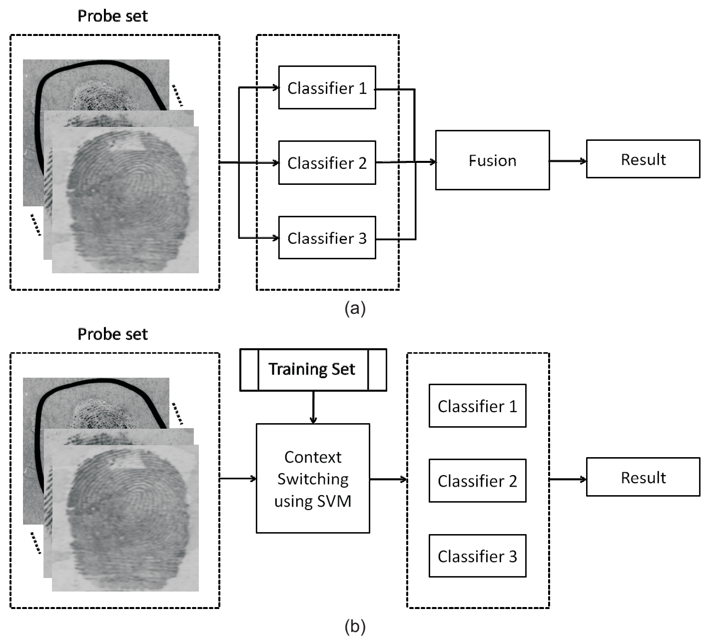


Figure 3: Two frameworks for latent to latent fingerprint matching (a) fusion and (b) context switching.

2. Latent to Latent Fingerprint Matching

Since matching latent to latent fingerprints is not a well studied problem, it is imperative to begin with analyzing the performance of existing approaches.

2.1. Matching using Individual Classifiers

Three different fingerprint feature extractors and matchers are used in this paper. The first classifier is the NIST Biometric Image Software (NBIS) [2], where the MINDTCT minutiae extractor and BOZORTH matcher are used. The second classifier is VeriFinger, a minutiae based commercial proprietary system developed by Neurotechnology [3]. The third classifier is a ridge flow based FingerCode algorithm [11][2]. These fingerprint classifiers are used because of their robustness and low cost/free availability.

2.2. Fusion Rules

Fusion is performed at match score and decision level as shown in Figure 3. At decision level, OR fusion rule [16] is performed by combining the classification decisions of all three algorithms. The match score level fusion is accomplished using the product of likelihood ratio (PLR) fusion [14]. For each classifier, match scores are modeled as a multivariate Gaussian distribution. The parameters of the distribution are obtained from the training set. The posterior

[1]Available for download at http://research.iiitd.edu.in/groups/iab/resources.html

[2]The MATLAB code of this algorithm is provided by Luigi Rosa [15].

probabilities of a probe being genuine and impostor are calculated and product of likelihood ratio is computed to make the decision.

2.3. Context Switching

Inspired from [18], SVM-based [7] context switching framework is used to dynamically select one of the three fingerprint classifiers. Since the experiment is performed in identification mode, the SVM is parameterized by the probe information only. Two parameters are chosen for context switching: (a) NFIQ scores and (b) number of minutiae. Since NFIQ is one of the state-of-art fingerprint quality metrics publicly available and there is a lack of other such (publicly available) quality metrics, the first context switching approach is based on NFIQ scores. The training data are first labeled to represent that for a given NFIQ score, which classifier can be used. SVM is then trained using these NFIQ scores to select the best classifier for matching. In other words, for a given probe image with a specific NFIQ score, SVM selects the algorithm that can yield the best accuracy. The second approach uses minutiae count in place of NFIQ for context switching. In this approach, the best algorithm is selected based on the number of minutia points. Though one of the parameters in NFIQ is based on minutiae, it is observed that in latent fingerprint matching, minutiae count based context switching performs better (results are presented in Section 4).

3. Database

In this research, two databases have been used. The first database is a publicly available Multi-Latent database [1]. It contains latent fingerprint and exemplars of four subjects with all ten fingers making it 40 classes. The latent impressions are 1000ppi images while both 500ppi and 1000ppi resolution exemplars are available, thus allowing analysis of consistency of features between images. The quality of latent fingerprints covers a broader spectrum compared to NIST 27SD [4].

The second database is the IIIT-D Latent fingerprint database prepared by the authors. It consists of latent fingerprints pertaining to 15 subjects with all 10 fingerprint, thus the database has 150 classes (assuming each fingerprint is unique and independent). The latent fingerprints are captured under semi controlled environment the black powder dusting process. Further, the database is prepared in multiple sessions with variations in background (tile and ceramic plate) and captures the effect of dryness, wetness, and moisture. This provides ample variation in the quality, noise and information content of latent fingerprints. The images of lifted latent fingerprints are captured using a *Canon EOS 500D* camera at a resolution of 4752×3168 (15 Mega pixels resolution). In total, there are 1046 latent fingerprints corresponding to 150 classes.

Table 1: Number of latent images in each database.

Database	Gallery	Training	Testing
IIIT-D Latent database	395	131	520
Multi-Latent database	40	26	100

Table 2: Rank-10 identification accuracy on the IIIT-D Latent database.

Algorithm	Accuracy(%)
NBIS	58.9
VeriFinger	74.0
FingerCode	35.4
Decision Fusion	77.7
PLR Fusion	55.8
Context Switching (Quality)	40.4
Context Switching (Number of minutiae)	58.7

Table 3: Rank-10 identification accuracy on the Multi-Latent database.

Algorithm	Accuracy(%)
NBIS	29.7
VeriFinger	41.9
FingerCode	38.0
Decision Fusion	70.9
PLR Fusion	42.1
Context Switching (Quality)	29.3
Context Switching (Number of minutiae)	48.2

4. Experimental Results

The experiments are performed individually on both the databases and the number of latent images in each database is provided in Table 1. The Multi-Latent database contains a total of 166 latent fingerprints while the IIIT-D Latent database contains 1046 latent fingerprints. The Multi-Latent database has multiple instances of varying quality latent prints for each class. One good quality latent fingerprint (manually selected) from each of the 40 classes is chosen as the gallery, 26 images are used for training, and the remaining 100 images are used as the probe. For the IIIT-D Latent database, 395 images are randomly chosen as the gallery, 131 images are used for training, and the remaining are used as probe. For any class, if there is only one image, then it is included in the gallery.

Both PLR match score fusion and SVM context switching require training. From both the datasets, total of 157 images are used for training. Note that the training data

Table 4: Correlation among match scores of classifier pairs in the IIIT-D Latent database.

	NBIS	VeriFinger	FingerCode
NBIS	1	-5.10E-04	-0.0880
VeriFinger	-5.10E-04	1	0.0021
FingerCode	-0.0880	0.0021	1

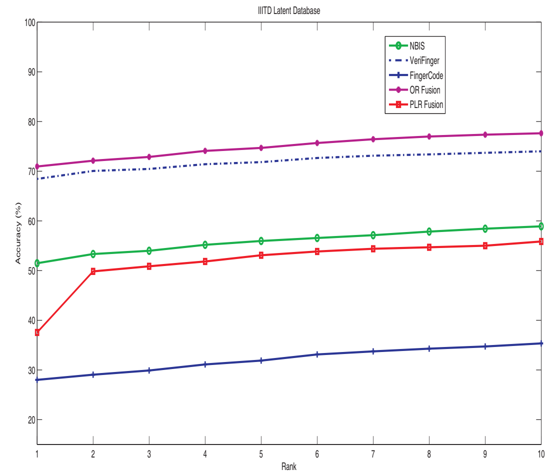
Table 5: Correlation among match scores of classifier pairs in the Multi-Latent database.

	NBIS	VeriFinger	FingerCode
NBIS	1	0.9715	-0.1325
VeriFinger	0.9715	1	0.1130
FingerCode	-0.1325	0.1130	1

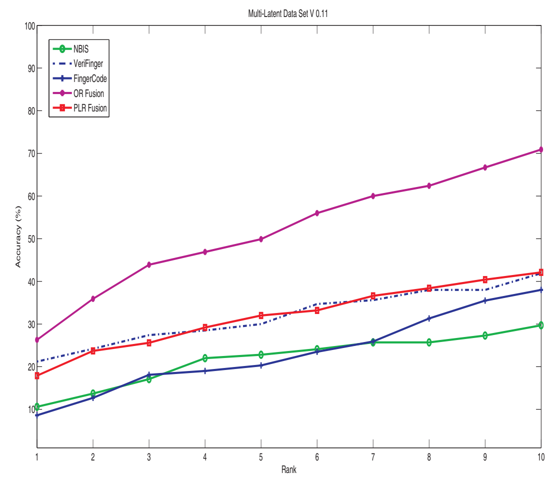
provided to the algorithm is very small and the quality of training images is also not ensured. The experiments are performed in identification mode with 10 times repeated random sub-sampling cross validation. Further, no pre-processing has been performed on the latent fingerprints. Tables 2 and 3 show the rank-10 identification accuracy and Figure 4 shows the Cumulative Match Characteristic (CMC) curves on the IIIT-D Latent database and Multi-Latent database, respectively.

4.1. Performance of Individual Classifiers

For both the databases, VeriFinger provides the maximum accuracy. Though VeriFinger provides facilities to set constraints on the image quality, minimum number of minutiae etc., all these constraints are not used to make it comparable to the other two classifiers. The correlation among match scores of different pairs of classifiers is also calculated (Tables 4 and 5). For the IIIT-D Latent database, it is observed that the correlation between classifiers is very low. On the other hand, for the Multi-Latent database, the correlation between NBIS and VeriFinger is very high, whereas the correlation of NBIS and VeriFinger with FingerCode is low. One possible explanation for this could be: when there is large variation in the quality and content of the image, both the minutiae-based algorithms capture similar information whereas the ridge-based algorithm captures different information. The presence of this complementary information inspired us to perform context switching, explained later in this section. Figure 5(a) shows two images for which the minutiae based algorithm performed correctly while the ridge flow based algorithm failed and Figure 5(b) shows two sample images for which the ridge flow based algorithm performed correctly while the minutiae based algorithm failed. It is observed that, if more number of minutiae



(a)



(b)

Figure 4: CMC curves for the (a) IIIT-D Latent database and (b) Multi-Latent database.

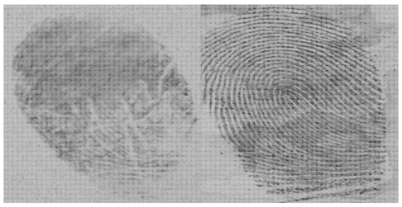
can be extracted with confidence, the minutiae-based classifier works better. Also, from match score correlation, it can be observed that obtaining minutiae features and ridge flow information are independent of each other.

4.2. Performance of Fusion Algorithms

Individual classifier decisions are combined using the OR decision fusion rule. Tables 2 and 3 show that the OR rule yields the highest maximum accuracy of 77.67% on the IIIT-D Latent data set and 70.9% on the Multi-Latent data set. Even though OR rule provides maximum performance for this experiment, the computational complexity of the complete process is higher.

At match score level, PLR fusion combines the score obtained from individual fingerprint classifiers. Surprisingly,

(a) For Minutiae



(b) For Ridge flow

Figure 5: Sample latent fingerprint images. For fingerprint images in (a) minutiae-based classifier yields correct result and ridge flow classifier fails. For fingerprint images in (b) ridge flow classifier yields correct result and minutiae-based classifier fails.

Figure 6: Sample latent fingerprint images for which SVM based context switching procedure fails whereas Decision level OR fusion gives correct results.

for this particular experiment, the accuracy of PLR fusion drops down to 55.83% for the IIIT-D Latent database and 44.1% for the Multi-Latent data set. Two possible explanations for the reduction in accuracy can be,

- Modeling the distributions as multivariate Gaussian does not correctly generalize the data and a better model should be obtained.
- For some cases, it is observed that the results provided by the three classifiers are contradictory and therefore the fusion of match scores yields incorrect results.

4.3. Context switching based on SVM

To avail the complementary information available from the match scores of different classifiers, a context switching framework is utilized to choose between one of the three algorithms. In other words, for a given probe image, the framework should select which of the three classifiers is more likely to correctly classify the given image. SVM performs this context switching and it is trained using the training set of latent fingerprints. The parameters chosen for context switching are (i) fingerprint quality score provided by NFIQ and (ii) number of minutiae provided by NBIS. The experiments are performed individually with both the parameters.

With quality score, SVM is formulated as a four class problem i.e., one of the three classifiers can classify it and none of the classifiers can classify it. The fourth class is comparable to recall percentage of a system and is useful when the test image is not a fingerprint or is of very poor quality. The accuracy of context switching for the IIIT-D Latent database is 40.39% and for the Multi-Latent database is 29.3%.

With number of minutia points as the parameter, SVM is formulated as a three class problem with the classes being a minutiae based algorithm, a ridge based algorithm and neither of the two. MINDTCT algorithm of NBIS provides the minutiae of each image along with a confidence value of each minutiae. A threshold of 50% is applied on the confidence of minutiae (to remove spurious minutiae) and the minutiae greater than this threshold are selected. The hypothesis is, when more number of minutiae are detected in an image, a minutiae based algorithm is chosen for classification otherwise a ridge correlation based algorithm is selected. The decision boundary is learnt using SVM which provides rank-10 identification accuracy of 58.7% on IIIT-D Latent database and 48.2% on the Multi-Latent database.

Manual inspection of images is performed to analyze the subset of latent fingerprint images for which SVM based context switching framework does not work. Figure 6 shows sample images for which the SVM based context switching framework fails whereas the decision level OR-fusion provides correct result (i.e., one of the classifiers can correctly classify the fingerprint). Observation on images and results show that the image quality and features do have an impact on the selection of classifiers. However, the correct parameters or the correct combination of parameters is required to properly perform context switching among the classifiers.

5. Conclusion and Future Work

This research presents an analytical understanding of latent to latent fingerprint matching. We evaluated the performance of existing feature extraction and matching approaches along with decision fusion using OR rule, PLR match score fusion, and SVM-based context switching algorithms. We also present a latent fingerprint database that is made accessible to the community for further research. Following conclusions are drawn from this research:

- latent to latent fingerprint is an important research problem that requires comprehensive research,

- though context switching is a good option to achieve better accuracy with lesser time complexity, both image quality and number of minutiae points are not suitable parameters to switch among the classifiers. It is necessary to explore other parameters that could better exploit the sophistication of the context switching framework.

6. Acknowledgement

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