Hierarchical Fusion for Matching Simultaneous Latent Fingerprint

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Abstract

Simultaneous latent fingerprints are a cluster of latent fingerprints that are concurrently deposited by the same person. Inherent challenges of latent fingerprints such as partial and smudgy ridge flow information and presence of background noise, makes it challenging to develop an automated system. Simultaneous latent fingerprints, that are collection of fingerprints simultaneously deposited on the surface, makes use of context information along with the features of individual latent fingerprints. Simultaneous latent matching is therefore more challenging as there is a lack of automated or semi-automated technique to aid this process. The contribution of this paper is two-fold: (i) an automated hierarchical fusion approach is proposed for fusing evidences from multiple latent impressions, and (ii) a simultaneous latent fingerprint database is prepared to drive research in this problem. The proposed algorithm yields promising results on the simultaneous latent fingerprint database.

1. Introduction

Fingerprints that are deposited on surfaces by contact with human hands, known as latent prints, are one of the elementary evidences used by forensic experts. When a surface is touched or an object is held in hand, it is very likely that more than one finger comes in contact with the object. Multiple latent fingerprints deposited at the same time, produce together a chain of evidences and are called as *simultaneous latent fingerprints*. Scientific Working Group on Friction Ridge Analysis, Study and Technology (SWGFAST) glossary defines a simultaneous impression as *"two or more friction ridge impressions from the same hand or foot deposited concurrently"*. Figure 1 shows samples of simultaneous latent impressions.

Simultaneous latent fingerprint matching is essentially combining the information available in the individual latent fingerprints. Traditionally, latent fingerprints are manually matched against a gallery using the ACE-V methodology i.e., Analysis, Comparison, Evaluation, and Verification [7].

Figure 1. Simultaneous latent fingerprint impressions.

Simultaneous latent fingerprint examination is a complex application of ACE-V, where establishing simultaneity and utilizing multiple latent prints are main steps.

Research in latent fingerprints is motivated from a real world criminal proceedings. In the Commonwealth v. Patterson 2005 case [4], four latent fingerprints were lifted from the crime scene. The fingerprints had six, five, two, and zero minutiae respectively and none of them complied with the recommended number of minutiae (eight), that is a basic requirement for matching using ACE-V methodology. Though the latent fingerprints individually did not satisfy the "magic number", after establishing simultaneity, the four latent prints together provided 13 minutiae. The forensic experts used these combined minutiae to establish identity. The data was eventually rejected in the court of law citing that, "the theory, science and procedure behind matching latent fingerprints as a group is not well established and do not follow Daubert Analysis" [3].

1.1. Literature Survey

The properties and the challenges of the latent fingerprint hold true for simultaneous latent fingerprint as well, apart from the inclusion of context information. Jain and Feng [11] provided a comprehensive analysis of latent fingerprint matching. A semi automated approach was used in which both level 2 and level 3 features for latent fingerprint were manually marked. 258 latent fingerprints from NISTSD27 are used to match against 29257 rolled fingerprints obtained from a combination of NIST SD-27, NIST SD-4, NIST SD-

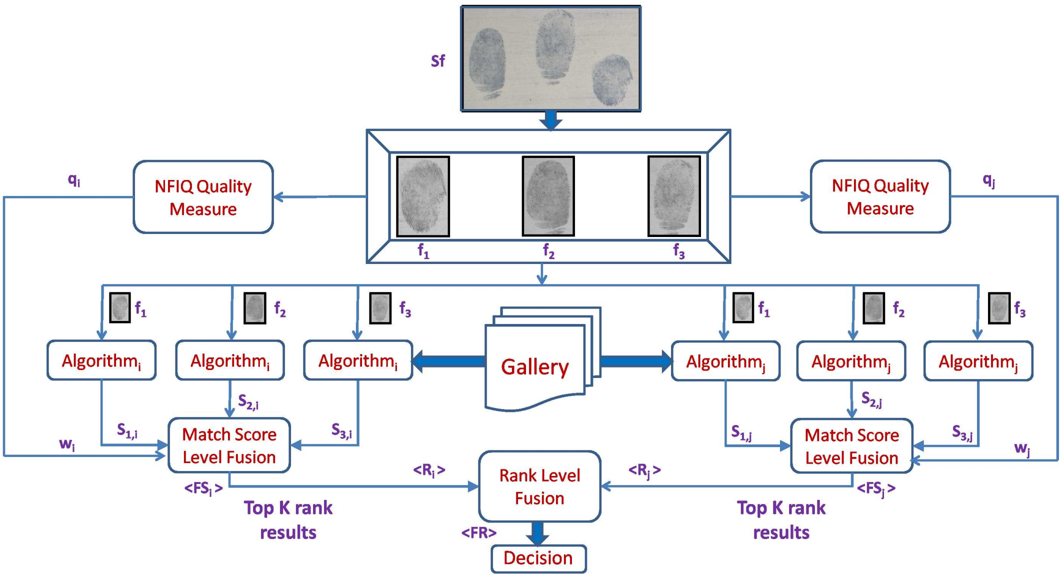

Figure 2. Illustrating the steps involved in the proposed two level hierarchical fusion framework.

14 databases. The accuracy increased from 34.9% for only level-2 features to 74% when extended features were used. Choi et al. [9] quantified the evidential value of latent fingerprints to establish the individuality so that it can be used as a forensic evidence. The match score modeling method explicitly made use of the prior odds to evaluate the evidential value. The goal towards latent fingerprint automation was strengthened when Zhang et al.[16] proposed an adaptive total variational model for automated latent fingerprint segmentation. The proposed method removed structured noise from the background and detected the Region Of Interest (ROI) of the latent fingerprint.

The process of extending applications of latent fingerprint to simultaneous latent fingerprint is not well studied. In 2006, Black [8] conducted the first experiments to study the application of ACE-V methodology for simultaneous impressions. The hypothesis was that a user (latent examiner) after a complete analysis of the simultaneous latent fingerprint, could establish the simultaneity. A collection of 30 latent fingerprint was used and the examiners manually applied the ACE-V method to establish the simultaneity of latent fingerprints. In their experiments, 88% of the times, the examiners correctly established the simultaneity. Further, in 2008, SWGFAST [5] released the standards for simultaneous latent impression matching that provided the well documented rules for establishing simultaneity in latent fingerprints and suggested guidelines for matching simultaneous impressions.

In 2009, Vatsa et al. [14] proposed the first semi-automated technique for simultaneous latent fingerprint matching. In their approach, latent examiners manually established the simultaneity and marked the features. They showed an improved accuracy of 58.1% using simultaneous latent fingerprint matching compared to the individual latent fingerprint matching accuracy of 28.6%. In 2011, Vatsa et al. [15] extended their approach and demonstrated improvement in both matching accuracy and computational time by applying a framework to prune the search for manual matching.

1.2. Research Contributions

This research focuses on developing a hierarchical fusion framework to establish identity using simultaneous latent fingerprints. The contributions of this paper can be summarized as follows:

1. A simultaneous latent fingerprint database, IIITD SLF (Simultaneous Latent Fingerprint) database together with mated optical fingerprint is prepared to motivate further research in this area.

2. A hierarchical fusion framework that combines match score fusion with rank fusion is proposed for assimilating information from simultaneous latent impressions.

2. Two Level Fusion Framework

The fundamental principle of simultaneous latent fingerprint matching is to combine the evidence present in the multiple latent fingerprints, thereby increasing the amount of information available for matching. The information from fingerprints can be combined at multiple levels - data level, feature level, match score level and rank level. Data level and feature level fusion are least researched in latent fingerprints because of the established challenges in those domain [11] whereas match score fusion is the most researched. In the proposed hierarchical approach, multiple latent fingerprint evidences are first combined at match score level. *Top-k* rank (candidate) lists are generated using multiple algorithms and, at second stage, are fused at rank level using weighted Borda count method [6].

As shown in Figure 2, simultaneous latent impression is matched with optical gallery and fusion is performed at both match score level and rank level. The algorithm is explained as follows:

1. A simultaneous impression, Sf consists of multiple fingers f_n, ($n = 2, 3, 4$ or 5). The region of interest of each finger f_i, ($i \in n$) is manually marked and segmented.

2. Multiple feature extractors and matchers are used to match the latent probe against the optical gallery. Every constituent finger f_i is matched with the gallery using algorithm, $Algorithm_j$ ($j = 1 \ldots m$, $m =$ the number of algorithms) and a set of scores $S_{i,j}$ is calculated.

3. In the first level of fusion, the scores from multiple fingerprints of the same simultaneous impression, obtained using $Algorithm_j$, are combined using match score level fusion that also incorporates quality of the image. For a finger f_i, its NFIQ quality [1] is measured as q_i, $q_i = 1, 2, \ldots, 5$. In NFIQ scale, quality score 1 denotes the highest quality. We need to assign larger weight for a fingerprint with better quality; the inverse of quality score can be considered as the weighting factor for a fingerprint. Therefore, the weight of a fingerprint is derived from its NFIQ score, $w_i = 10/q_i$ and it can have five discrete values, $w_i = [10, 5, 3.33, 2.5, 2]$. The fused score for $Algorithm_j$ can be computed using any existing match score fusion rule. In this research, we have used (1) weighted sum rule [7] and (2) product of likelihood ratio (PLR) fusion [12]. The fused score is computed using the weighted sum fusion as shown in equation 1.

$$FS_j = \sum_{i=1}^{n} (w_i \times S_{i,j}) \tag{1}$$

The fused score for $Algorithm_j$ is computed using the weighted PLR fusion [12] as shown in equation 2.

$$FS_j = \prod_{i=1}^{n} (w_i \times LR(S_{i,j})) \tag{2}$$

where LR represents the likelihood ratio defined by

$$LR(\cdot) = \frac{\hat{f}_{gen}(\cdot)}{\hat{f}_{imp}(\cdot)} \tag{3}$$

$\hat{f}_{gen}(\cdot)$ and $\hat{f}_{imp}(\cdot)$ denotes the probability of a match score being genuine and imposter respectively.

4. In identification mode, this process is repeated for all the subjects in gallery and $Algorithm_j$ provides a rank list R_j. The first level of fusion attempts to increase the amount of information used for decision making by fusing match scores from multiple evidences.

5. The second level of fusion combines the results from multiple algorithms at the rank level. This level of fusion attempts to combine multiple classifier information extracted from the same evidence. As illustrated in Figure 2, top-k rank matches from m different algorithms, R_j, are fused at rank level using weighted Borda count fusion [6]. For a simultaneous impression, the Borda count fusion method yields a fused rank list as,

$$FR = \sum_{j=1}^{m} (w \times R_j) \tag{4}$$

$$w = max(10/q_g, 10/q_p) \tag{5}$$

where q_g and q_p are the NFIQ quality measures of gallery and probe fingerprints respectively. The classification decision for the given probe Sf is then taken based upon the fused rank list, FR.

3. Database

Lack of availability of simultaneous latent fingerprint database for research is one of the main reason for limited research in this domain. To motivate research in this area and to encourage researchers to publish results on a common database, we have prepared IIITD SLF database[1], which is the largest and only publicly available database up till now. The setup with which the fingerprints are lifted is explained below.

Dusted latent fingerprints are usually lifted from the surface using tapes, stored in cards, and scanned using optical scanners. Lifting fingerprints using tapes introduces a *non-linear distortion* in ridge flow and is subjected to the expertise of fingerprint examiners. To minimize the error introduced during this lifting procedure, a camera setup is created (as shown in Figure 3) that captures the dusted fingerprint directly. The camera setup consists of a USB programmable camera that has a resolution of 3840×2748. It has a 1/2" CMOS sensor and captures at a maximum rate of 3 frames per second. A manual C-Mount CCTV lens having a focal length of 8mm is mounted on the camera which

[1] `http://research.iiitd.edu.in/groups/iab/fpdatabases.html`

Figure 3. Camera setup for IIITD SLF database capture.

provides finer focus for capturing the latent fingerprint. An illumination ring is attached around the camera to enhance the capture quality.

A sample fingerprint of the database is provided in Figure 4. Multiple samples of various finger combinations are collected from 30 subjects in a semi-controlled environment with a ceramic tile as the background, i.e. fingerprints are deposited on a ceramic tile. The database collection process ensures that both latent fingerprint deposition and lifting is done simultaneously. Hence, simultaneity is established as a ground truth in this database. Further, two sets of mated optical slap fingerprints (4 + 4 + 2 fingers) are captured using Crossmatch L-Scan Patrol at 500 dpi for all 30 subjects. The database provides scope of research in both matching simultaneous latent fingerprints and establishing simultaneity automatically. Detailed statistics of the IIITD SLF database are given in Table 1.

(a) Simultaneous Latent Fingerprint of left hand

(b) Simultaneous Latent Fingerprint of right hand

(c) Fingerprint captured using CrossMatch

Figure 4. Sample fingerprint of one subject in the database.

Number of subjects	30
Number of classes	60 (2 hands per subject)
Number of simultaneous latent samples per class	6
Total Number of simultaneous impressions	360
Total number of latent fingerprints	1080
Number of optical slap impressions (4 + 4 + 2 prints)	60

Table 1. Details of the IIITD SLF database.

4. Experimental Results

To evaluate the effectiveness of the proposed algorithm, simultaneous latent fingerprint probe images from the IIITD SLF database are matched with a gallery of optical slap fingerprints. To make the latent matching environment more challenging and realistic, 2000 optical fingerprints pertaining to 100 subjects from the MCYT database [13] are added to the gallery. The extended gallery consists of 2600 optical fingerprints from the IIITD SLF and MCYT databases. Further, 20% of the database is used for training and rest are used for testing. The experimental protocol is given in the Table 2.

	Gallery	**Probe**
Total	2600	1080
Train	120	216
Test	2480	864

Table 2. Number of images in the experimental setup.

Matching of individual latent fingerprints against the optical images is provided as the baseline accuracy of the database and the results of the fusion model is built upon it. Three different algorithms are used in the experiment: (1) NBIS [1] is an open source minutiae based algorithm, (2) VeriFinger [2] is a commercial minutiae based algorithm, and (3) FingerCode [10] is a ridge flow based matching algorithm. The results of match score fusion are provided in Table 3 and Cumulative Match Characteristic (CMC) curves are shown in Figures 6 to 8. The rank list generated after weighted sum score fusion by multiple algorithms is fused at rank level using weighted Borda count. The results of the second stage rank level fusion are tabulated in Table 4 and CMC curves are shown in Figure 9. The key results are as follows:

1. From Table 3, it can be observed that NBIS performs better for individual latent fingerprints without fusion. Weighted sum rule improves the matching performance for NBIS and VeriFinger and the best possible accuracy is obtained for NBIS (24.14%).

2. Weighted PLR fusion fails uniformly for all algorithms because of the lack of training data available to calculate the parameters of the Gaussian model.

3. As the amount of minutiae information increases, the rank level fusion shows improved accuracy for NBIS-VeriFinger. This observation is also reflected in the rank list of the matching algorithms.

4. It is observed that fusion techniques fail uniformly for FingerCode based approach because of the nature of ridge features. It is our assertion that in latent fingerprints, artifacts such as noisy background and sunglasses affect ridge features and thus lead to reduced performance.

5. From Table 5 it can be observed that the average number of minutiae increases when the simultaneous latent fingerprints are combined into a single sample.

6. The average number of minutiae generated by NBIS is 3 and 8 for latent and simultaneous latent fingerprints respectively whereas VeriFinger generates about 29 and 86 minutiae. However, the matching accuracy of VeriFinger is lower than that of NBIS. This shows that, on this database, VeriFinger generates several spurious minutiae.

7. Figure 5(a) shows an example where the individual algorithms failed to individualize the latent fingerprints, whereas the proposed fusion framework (with NBIS-VeriFinger fusion) could classify it correctly at rank 2. Figure 5(b) shows a failure example, where NBIS algorithm could correctly individualize the latent fingerprints, whereas the fusion framework fails to do so.

(a) Success case

(b) Failure case

Figure 5. Sample cases of success and failure of the proposed hierarchical fusion algorithm.

	Without fusion (%)	Weighted Sum Fusion (%)	Weighted PLR Fusion (%)
NBIS	16.07	24.14	10.35
VeriFinger	11.00	13.54	12.40
FingerCode	11.95	10.42	09.38

Table 3. Rank 10 accuracy of match score level fusion experiments.

	Rank 10 Accuracy (%)
NBIS-VeriFinger	27.59
NBIS-FingerCode	12.85
VeriFinger-FingerCode	21.88

Table 4. Rank 10 accuracy of rank level fusion experiments.

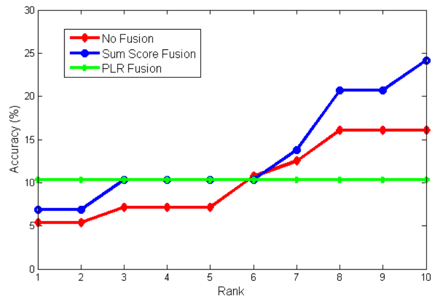

Figure 6. CMC plot of NBIS algorithm comparing different match score level fusion techniques.

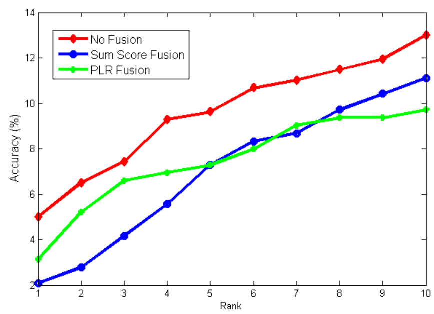

Figure 7. CMC plot of FingerCode algorithm comparing different match score level fusion techniques.

Fingerprint matcher		Max	Min	Mean
Optical	NBIS	119	19	63
	VeriFinger	79	5	40
Latent	NBIS	76	0	3
	VeriFinger	92	0	29
Simultaneous latents	NBIS	155	0	8
	VeriFinger	234	0	86

Table 5. Number of minutiae extracted from the IIITD SLF database.

Comparison with Existing Approaches: Both Black [8] and SWGFAST [5] primarily focus in establishing the simul-

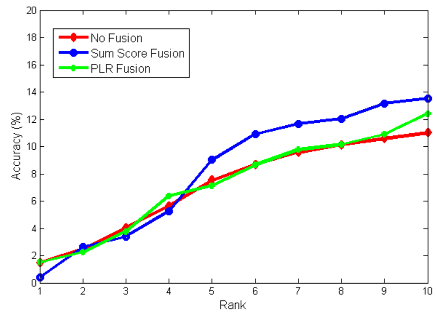

Figure 8. CMC plot of VeriFinger algorithm comparing different match score level fusion techniques.

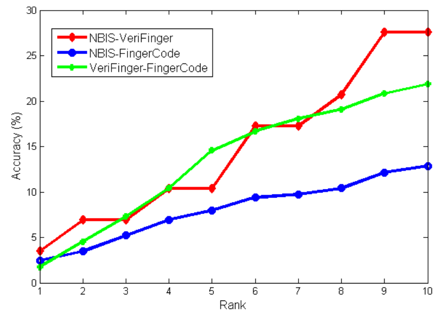

Figure 9. CMC plot for rank level fusion of algorithms.

taneity of the latent fingerprints. ACE-V methodology suggests that comparison and evaluation of latent fingerprints can be performed after analyzing the simultaneity of latent fingerprints. The semi-automatic approach for simultaneous latent fingerprint matching proposed by Vatsa et al. [15] shows good results on a private database obtained from law enforcement agencies. In comparison to these existing studies, this research (1) presents the IIITD SLF database that is publicly available to the research community and (2) proposes a hierarchical fusion approach using existing open source and commercial tools to improve the performance of simultaneous fingerprint recognition.

5. Conclusion and Future Work

There is limited research in simultaneous latent fingerprint matching. In our opinion, this is primarily due to the absence of publicly available simultaneous latent database and lack of reliable automated feature extraction and matching algorithms for latent fingerprints. This paper highlights the existential necessity for a reliable automated or semi-automated system for matching simultaneous latent fingerprints. A two-level fusion framework is proposed to combine information both at the match score and rank levels. This research also presents the first publicly available simultaneous latent fingerprint database (along with mated optical sensor images). The results on the IIITD SLF database suggest that fusion techniques can be effectively used in matching simultaneous ridge impressions. The algorithm can be further improved by (1) including context specific geometrical and spatial information provided by the simultaneous latent fingerprints and (2) improving feature extraction and matching algorithms.

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