ON SIMULTANEOUS LATENT FINGERPRINT MATCHING

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ABSTRACT

Simultaneous latent fingerprints are a cluster of latent fingerprints that are concurrently deposited by the same person. Though ACE-V methodology provides the scientific basis for matching latent fingerprints, extending it for simultaneous latent fingerprints is challenging. Further, there is a lack of automated or semi-automated algorithms to aid this process. The contribution of this paper is two-fold: (i) an automated two-level fusion technique for fusing evidences from multiple ridge impressions, and (ii) a simultaneous latent fingerprint database is created to drive research in this problem. The proposed algorithm yields promising results on the simultaneous latent fingerprint database.

Index Terms— simultaneous latent fingerprints, multi-level fusion

I. INTRODUCTION

Latent fingerprints deposited on surfaces that come in contact with human hand are one of the elementary evidences used by forensic experts. Further, multiple latent fingerprints that are deposited at the same time, produce together a chain of evidence and are called simultaneous latent fingerprints. SWGFAST glossary defines a simultaneous impression as "two or more friction ridge impressions from the same hand or foot deposited concurrently". Fig. 1 shows samples of simultaneous latent impressions. Generally, the matching of latent fingerprint is manually performed against a gallery using the ACE-V methodology i.e., Analysis, Comparison, Evaluation, and Verification [1].

In the Commonwealth v. Patterson [2] case in 2005, four latent fingerprint were lifted from the crime scene. The fingerprints had six, five, two, and zero minutiae respectively and none of them complied

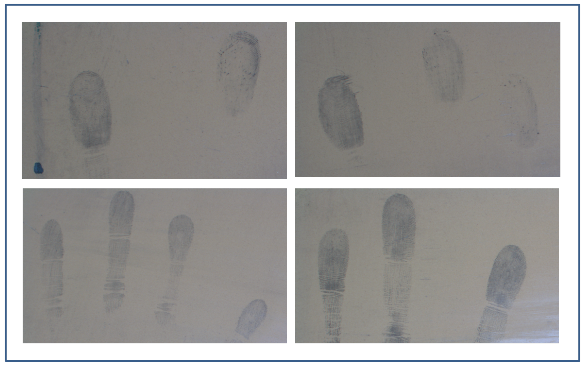

Fig. 1. Simultaneous latent fingerprint impressions.

with the minimum 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 individuality. 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 did not follow Daubert Analysis [3].

In 2006, Black[4] first conducted experiments to study the application of ACE-V methodology for simultaneous impressions. In 2008, SWGFAST [5] released the standards for simultaneous impression matching. The standards provided the rules for establishing simultaneity in latent fingerprints and suggested guidelines for matching simultaneous impressions. In 2009, Vatsa et al. [6] proposed the first semi-automated technique for simultaneous latent fingerprint matching. In their approach, latent examiners manually established the simultaneity and marked the features. The research work showed an improved accuracy of 58.1% using simultaneous latent fingerprint matching compared to the stand alone latent fingerprint matching accuracy of 28.6%. In 2011, Vatsa et al. [7] demonstrated improvement in both matching accuracy and computational time by applying their framework to prune the search for manual matching. There is a lack of 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 research attempts to overcome these two limitations by making the following two contributions:

- A novel two-level fusion framework is proposed for fusing information from multiple ridge impressions.

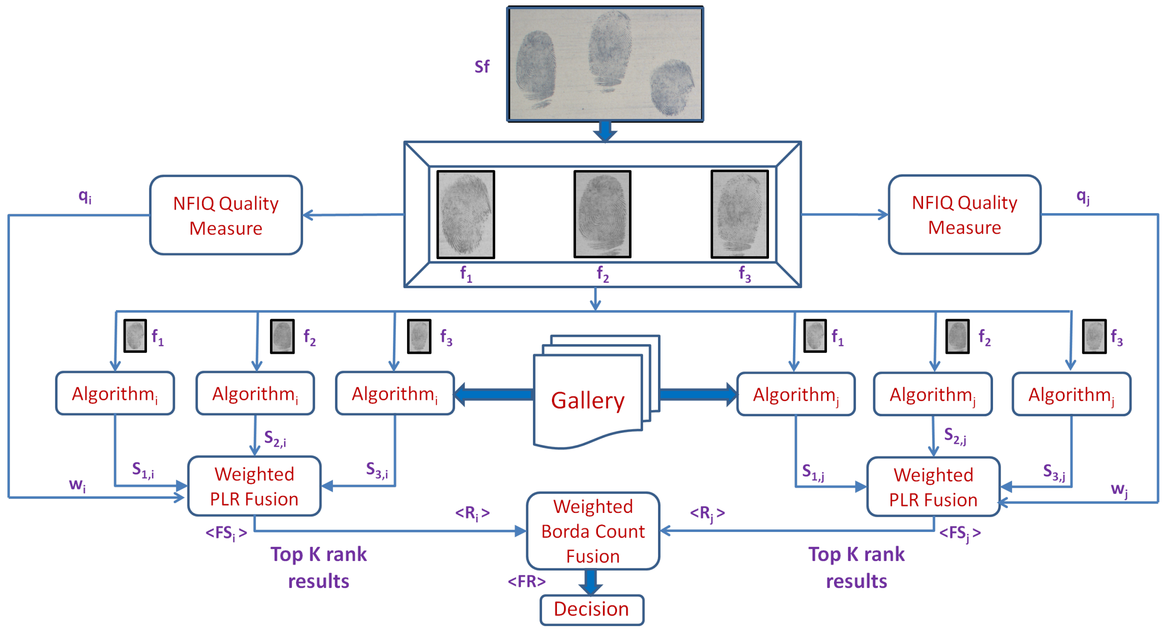

Fig. 2. Illustrating the steps involved in the proposed two level fusion approach.

- A new simultaneous latent fingerprint database, termed as the IIITD Simultaneous Latent Fingerprint (IIITD SLF) database, with mated optical fingerprint is created and provided publicly to motivate further research in this problem.

II. PROPOSED APPROACH

A multi-stage fusion framework for matching simultaneous latent impressions is proposed in this section. As shown in Fig. 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 features extractors and matchers are used to match the probe against the gallery. Every finger f_i is matched with the gallery using algorithm, $Algorithm_j$ (j = $1 \ldots m$ i.e., 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 a simultaneous impression, obtained using $Algorithm_j$, are combined using weighted PLR fusion [8]. For a finger f_i, its NFIQ quality [9] is measured as q_i, $q_i = 1, 2, \ldots, 5$. The weight for the fingerprint is derived from its NFIQ score as $w_i = 10/q_i$. Therefore weights can have five discrete values, $w_i =$

$[10, 5, 3.33, 2.5, 2]$. The fused score for $Algorithm_j$ is computed using weighted PLR fusion [8] as shown in equation 1.

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

where LR represents the Likelihood Ratio defined by

$$LR(\cdot) = \frac{\hat{f}_{gen}(\cdot)}{\hat{f}_{imp}(\cdot)} \tag{2}$$

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

4) The second level of fusion combines the results from multiple algorithms at rank level. This level of fusion attempts to combine multiple classifier information extracted from the same evidence. Top-k rank matches from j different algorithms, R_j are fused at rank level using weighted Borda count fusion [10]. For a simultaneous impression, the Borda count fusion method yields a fused rank list as,

$$FR = \sum_{j=1}^{m} (w \times R_j) \tag{3}$$

$$w = max(10/q_g, 10/q_p) \tag{4}$$

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.

III. IIITD SIMULTANEOUS FINGERPRINT DATABASE

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 Fig. 3) that captures the dusted fingerprint directly. The camera setup consists of a USB programmable UEye 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

Fig. 3. Camera setup for IIITD SLF database capture.

manual C-Mount CCTV lens having a focal length of 8mm is mounted on the camera which provides finer focus for capturing the latent fingerprint. An illumination ring is attached around the camera to enhance the capture quality.

IIITD Simultaneous Latent Fingerprint database is prepared using this setup. Multiple samples of various finger combinations are collected from 15 subjects in a semi-controlled environment with a ceramic tile as the background. 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 for all 15 subjects. The database provides scope of research in both matching simultaneous latent fingerprints and establishing simultaneity automatically. Details of the IIITD SLF database are given in Table I.

Number of subjects	15
Number of classes	30 (2 hands per subject)
Number of samples per class	8
Number of simultaneous impressions	240
Total number of latent fingerprints	720
Number of optical slap impressions	30 (4 + 4 + 2 prints)

Table I. Details of the IIITD SLF database.

IV. 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 [11] are added to the gallery. The gallery thus consists of 2300 optical fingerprints from the IIITD SLF and MCYT databases. Further, 12% of the database is used for training while the remaining is used as the testing dataset.

The matching of individual latent prints 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: NBIS [9] is an open source minutiae based algorithm, VeriFinger [12] is a commercial minutiae based algorithm, and FingerCode [13] is a ridge flow based matching algorithm. An empirically calculated 50% threshold is applied on the confidence of minutiae obtained using NBIS. The performance of weighted PLR fusion is also compared with weighted sum score fusion and the results are provided in Table II and Fig. 6. The results of the second level fusion method are tabulated in Table III and the CMC plots are shown in Fig. 7. The key analysis are as follows:

1) The rank level fusion shows improved accuracy for various algorithm pairs except for the NBIS-VeriFinger combination. The similar performance of fusion algorithm and NBIS can be attributed to the fact that both NBIS and VeriFinger are minutiae based algorithms and there is no complementary information to combine.
2) From Table IV it can be observed that the average number of minutiae increases when the simultaneous latent fingerprints are combined into a single sample.
3) The average number of minutiae generated by NBIS is 5 and 15 for latent and simultaneous latent fingerprints respectively whereas VeriFinger generates about 31 and 93 minutiae. This shows that VeriFinger generates a lot of spurious minutiae.
4) The PLR fused matching accuracy of VeriFinger is found to be very low when compared with NBIS (at 50%) because of the lot many spurious minutiae generated.
5) On fusing the results of VeriFinger with FingerCode at rank level, it is observed that the accuracy increases to 45.31%. Rank level fusion captures this complementary information and enables better decision making capability. However, fusion of NBIS with FingerCode suggests that presence of noisy results can actually decrease the performance of fusion.
6) Fig. 4 shows an example where the individual algorithms failed to individualize the latent finger-

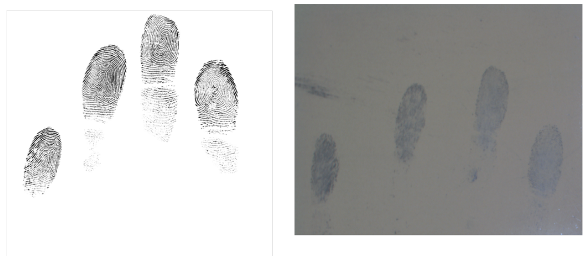

Fig. 4. Sample case of success of the fusion algorithm.

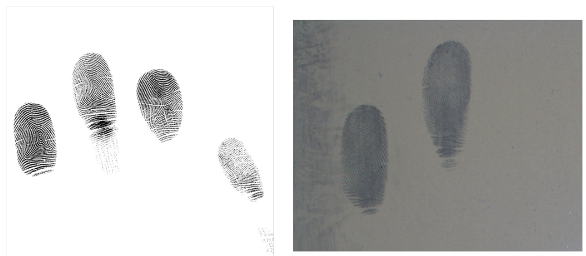

Fig. 5. Sample case of failure of the fusion algorithm.

prints, whereas the proposed fusion framework (having NBIS-VeriFinger fusion) could classify it correctly in rank 4. Fig. 5 shows a failure example, where NBIS algorithm could correctly individualize the latent fingerprints, where the fusion framework failed.

	No fusion (%)	Weighted Sum Fusion (%)	Weighted PLR Fusion (%)
NBIS	62.5	36.7	72.7
VeriFinger	21.3	19.8	18.2
FingerCode	21.5	19.1	18.0

Table II. Rank 15 accuracy of match score level fusion experiments.

	Rank 15 Accuracy (%)
NBIS-VeriFinger	72.7
NBIS-FingerCode	19.3
VeriFinger-FingerCode	30.7

Table III. Rank 15 accuracy of rank level fusion experiments.

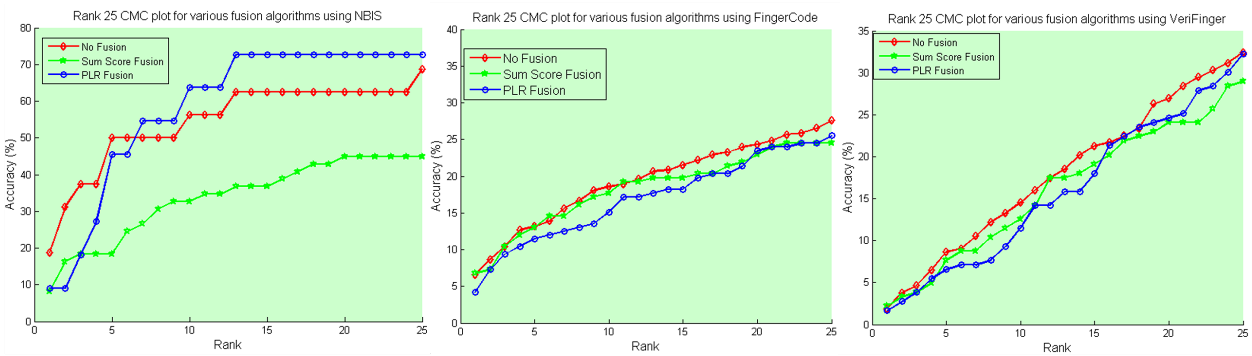

Fig. 6. CMC plot of matching algorithms comparing different match score level fusion techniques.

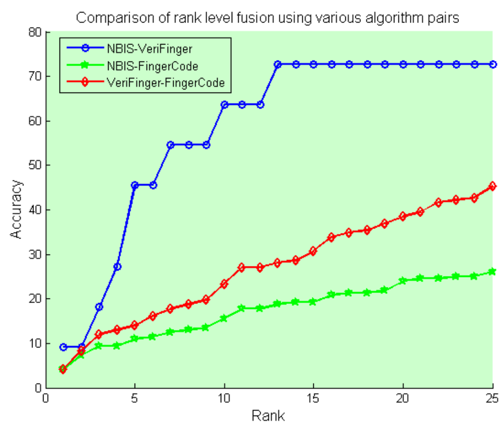

Fig. 7. CMC plot for rank level fusion of algorithms.

Finger print	**Matcher**	**Maximum**	**Minimum**	**Average**
	NBIS	119	19	61
Optical	NBIS (50%)	71	1	22
	VeriFinger	83	6	35
	NBIS	76	0	5
Latent	NBIS (50%)	26	0	2
	VeriFinger	92	0	31
Simult	NBIS	155	0	15
aneous	NBIS (50%)	68	0	5
Latents	VeriFinger	220	0	93

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

V. CONCLUSION AND FUTURE WORK

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 that attempts to combine information both at the match score and rank levels. The results suggest that fusion techniques can be effectively used in matching simultaneous ridge impressions. Preliminary results is provided for IIITD SLF database with a strong hope to motivate further research in this problem. 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.

VI. REFERENCES

[1] D.R. Ashbaugh, "Quantitative-Qualitative friction ridge analysis: An introduction to basic and advanced ridgeology," *CRC Press LLC: Boca Raton, FL*, pp. 134–135, 1999.

[2] "Commonwealth v Patterson," in *445 Mass. 626; 840 N.E.2d 12*, 2005.

[3] "Daubert v Merrell Dow Pharmaceuticals," in *Inc. 509 U.S. 579*, 1993.

[4] J.P. Black, "Pilot study: The application of ACE-V to simultaneous (cluster) impressions," *Journal of FI*, vol. 56, pp. 933–971, 2006.

[5] "SWGFAST, Standard for simultaneous impression examination, ver. 1.0," www.swgfast.org, 2008, pp. 1–20.

[6] M. Vatsa, R. Singh, A. Noore, and K. Morris, "Simultaneous latent fingerprint recognition: A preliminary study," in *IEEE BTAS*, 2009, pp. 1–5.

[7] M. Vatsa, R. Singh, A. Noore, and K. Morris, "Simultaneous latent fingerprint recognition," *Applied Soft Computing*, vol. 11, pp. 4260–4266, 2011.

[8] K. Nandakumar, Y. Chen, S. Dass, and A.K.Jain, "Likelihood ratio based biometric score fusion," *IEEE Transactions on PAMI*, vol. 30, pp. 342–347, 2008.

[9] "NBIS (NIST biometric image software)," http://www.nist.gov/itl/iad/ig/nbis.cfm.

[10] A. Abaza and A. Ross, "Quality based rank-level fusion in multibiometric systems," in *IEEE BTAS*, 2009, pp. 1–6.

[11] J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon, J. Gonzalez, M. Faundez-Zanuy, V. Espinosa, A. Satue, I. Hernaez, J.-J. Igarza, C. Vivaracho, D. Escudero, and Q.-I. Moro, "MCYT baseline corpus: a bimodal biometric database," in *IEE Proceedings on Vision, Image and Signal Processing*, 2003, vol. 150, pp. 395–401.

[12] “VeriFinger,” www.neurotechnology.com/verifinger.html.

[13] A.K. Jain, S. Prabhakar, L. Hong, and S. Pankanti, “Filterbank-based fingerprint matching,” *IEEE Transactions on IP*, vol. 9, pp. 846–859, 2000.