Latent Fingerprint from Multiple Surfaces: Database and Quality Analysis

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Abstract

Latent fingerprints are lifted from multiple types of surfaces, which vary in material type, texture, color, and shape. These differences in the surfaces introduce significant intra-class variations in the lifted prints such as availability of partial print, background noise, and poor ridge structure quality. Due to these observed variations, the overall quality and the matching performance of latent fingerprints vary with respect to surface properties. Thus, characterizing the performance of latent fingerprints according to the surfaces they are lifted from is an important research problem that needs attention. In this research, we create a novel multi-surface latent fingerprint database and make it publicly available for the research community. The database consists of 551 *latent fingerprints from* 51 *subjects lifted from eight different surfaces. Using existing algorithms, we characterize the quality of latent fingerprints and compute the matching performance to analyze the effect of different surfaces.*

1. Introduction

Latent fingerprints are crucial sources of evidence in the court of law to identify suspects. Currently, latent fingerprint matching is a semi-automated process, involving human efforts in feature extraction and verification of results [20]. However, human examination of latent fingerprint is a very laborious and time-taking process [22]. Thus, identifying the need for a completely automated "lights-out" matching system, with minimum or absolutely no human interference, FBI launched the Next Generation Identification (NGI) program [3]. One of the major challenge that hinders the growth of development of fully automated latent fingerprint matching algorithms is the presence of highly varying background noise. Typically, latent fingerprints can be lifted from a wide spectrum of possible surfaces from a crime scene, as shown in Figure 1. Some of the commonly found surfaces are wood, plastic, glass, paper, metal, and

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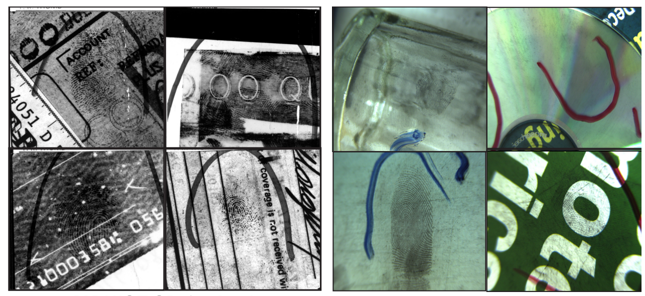

[A] NIST SD-27 database **[B] Proposed multi-surface latent fingerprint database**

Figure 1. Examples of latent fingerprint images from NIST SD-27 database and the proposed multi-surface latent fingerprint image database.

ceramic surfaces. The challenges introduced in latent fingerprint matching due to variations in surface can be summarized as follows:

- *Availability of partial fingerprint:* Due to the geometric variations in the background object and the surface type, latent fingerprints are generally partial and therefore limited information may be available for matching.
- *Presence of background noise:* Depending on the type, texture, quality, color, and shape of the background surface, varying amount of structured and unstructured noise are introduced. Thus, segmenting the foreground ridge region from the background is a challenge.
- *Poor quality ridge patterns:* The amount and quality of latent fingerprint deposited on the surface depends on the pressure applied. The applied pressure may also depend on the type of surface, resulting in smudgy and poor quality ridge patterns for matching.

It is important to characterize the quality of latent fingerprints with respect to the surface type in order to make a more informed match. In 2001, Lee and Gaensslen [12] provided a forensic perspective and insights for lifting of fingerprints from different surfaces. In 2012, Fischer et al. [9] studied latent fingerprints lifted from three surfaces: white

Table 1. Comparing the existing publicly available latent fingerprint databases.

Database	#Surfaces	#Subjects	#Images
NIST SD-27 [5]	NA	258	258
IIITD Latent [16]	2	15	1046
IIITD SLF [18]	1	30	1080
MOLF [21]	1	100	4400
Proposed	8	51	551

furniture, brushed metal, and car body finish, to conclude that the performance on planar, non-absorbing surfaces is better than the performance on non-uniform surfaces. However, to drive the research in this problem domain, there is no publicly available database containing latent fingerprints lifted from multiple surfaces. Also, it can be observed from Table 1 that existing publicly available latent fingerprint datasets do not include much variation with respect to the surfaces from which the prints are lifted (for NIST SD-27 [5] the surface information is not available). Recently in 2013, the report by National Research Council [4] also discussed this important challenge and suggested the need to characterize the accuracy of computer algorithms under the wide spectrum of variations in fingerprint impressions (Recommendation 12). Following this motivation, the major research contributions of the paper are as follows:

- create a novel multi-surface latent fingerprint database, containing 551 latent fingerprints lifted from eight surfaces,
- perform surface-wise quality estimation of latent fingerprints and study the performance of existing quality features across surfaces, and
- analyse the matching performance of latent fingerprints lifted from multiple surfaces.

2. Multi-surface Latent Fingerprint Database

Lack of multi-surface latent database is a major challenge in benchmarking the performance of the latent fingerprint matching system across multiple surfaces. The proposed database[1] contains 551 latent fingerprint images from 51 subjects with prints lifted from eight different surfaces. The surfaces are carefully chosen to introduce variations in surface albedo (reflectance), shape, texture, color, and amount of background noise involved. The eight surfaces along with their properties are as follows:

- **Ceramic plate**: Reflective, plane surface, non-porous, with white background.
- **Ceramic mug**: Reflective, curved surface, non-porous, with random text background.
- **Transparent glass**: Reflective, curved surface, non-porous, with transparent noisy background.
- **Steel glass**: Reflective, curved surface, non-porous, with uniform steel background.
- **Compact disc (CD)**: Reflective, plane surface, non-porous, with shiny background.
- **Compact disc mailer (CD mailer)**: Reflective, plane surface, non-porous, with transparent uniform background.
- **Paperback book cover**: Non-reflective, plane surface, non-porous, with random text background.
- **Hardbound book cover**: Reflective, plane surface, non-porous, with random text background.

Table 2. Characteristics of the proposed Multi-surface latent fingerprint database

Number of subjects	51
Number of classes	123 (at least 2/subject)
Number of latent print images	551
Number of surfaces	8
Resolution of latent fingerprints	3840×2748
Total slap fingerprint images	1020 (4+4+2)
Resolution of slap fingerprints	1600×1500

Seven out of the eight surfaces are reflective in nature, however, the extent of reflectivity varies across surfaces. For instance, the steel glass surface reflects more light than the other surfaces and often these reflections occlude the ridge patterns. The compact disk, due to its highly reflecting multi-colored background, seems to be the most difficult surface for imaging latent fingerprints. Depending on the amount of pressure applied on the surface and the adherence property of the surface to the natural secretions of the friction ridge skin, area of the deposited fingerprint varies considerably from surface to surface.

The contactless imaging setup used in this database collection is similar to the one used by Sankaran *et al*. [21]. We have used a programmable USB camera which has a $1/2$" CMOS sensor connected with manual C-mount CCTV Lens with a focal length of 6.5mm to 52mm and an aperture of $f/1.8$. The camera operates in a 8MP manual focus mode with controlled environmental illumination. The resolution of the images is 3840×2748. The entire camera setup is mounted on a tripod stand. Two different dusting powders are used to lift the latent fingerprint, depending on the surface: black powder and black magnetic powder. The magnetic powder was only used in the case of paperback book cover, as magnetic powder worked better in porous paper surface. The corresponding slap fingerprint $(4{+}4{+}2$ prints)

[1] Database: www.iab-rubric.org/resources/mlfpd.html

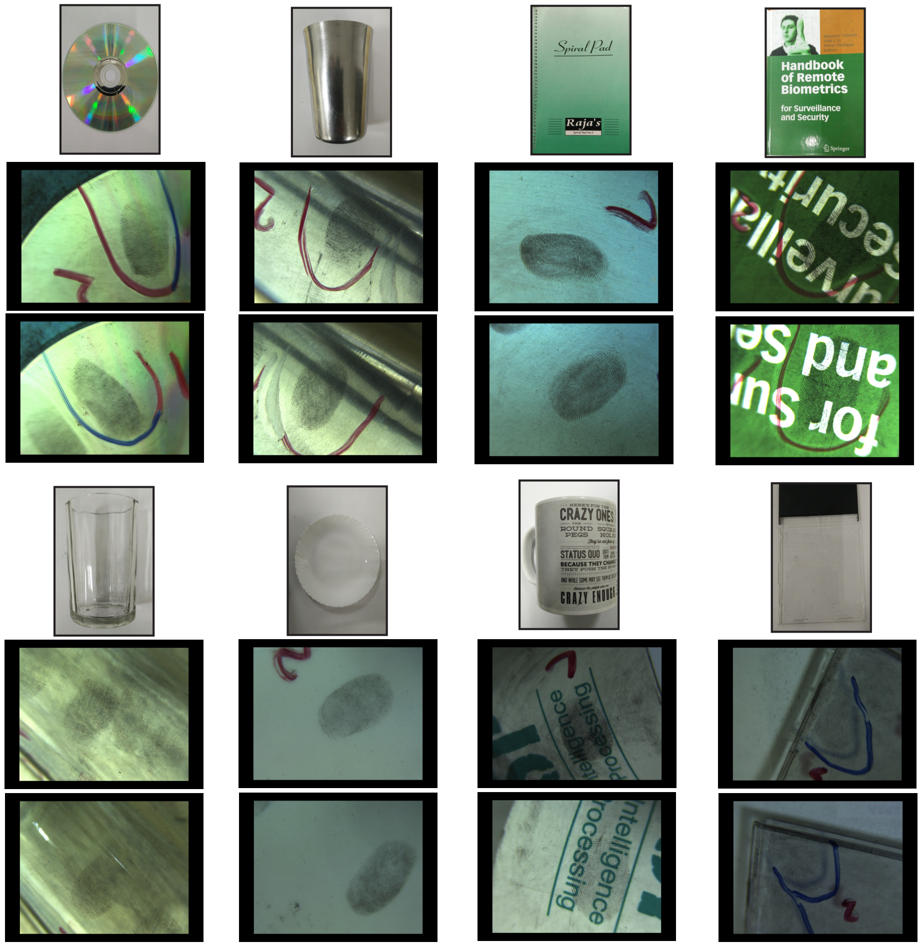

Figure 2. Two samples of latent fingerprint images lifted from the eight surfaces used in the database collection. (from left to right) First row: compact disc, steel glass, paperback cover, hardbound cover. Second row: transparent glass, ceramic plate, ceramic mug, compact disc mailer. (Best viewed in color and under zoom).

gallery images are captured using CrossMatch L-Scan Patrol at 500 dpi.

Every volunteer was requested to deposit latent fingerprints from at least two different fingers, and each finger was used on at least four different surfaces. External assistance was not provided to the user while depositing the latent fingerprints. Two sets of optical slap fingerprints were collected from each subject, one before depositing the latent fingerprints and one after depositing the latent fingerprints. The characteristics of the database are summarized in Table 2 and sample images are shown in Figure 2.

3. Quality Analysis

The quality of a latent fingerprint depends heavily on the surface on which it is deposited. Hence, it is very important to study the quality variations of latent fingerprints obtained from different surfaces in the proposed multi-surface latent fingerprint database. Various metrics have been proposed in literature to estimate the quality of a latent fingerprint [11, 13, 19, 24, 25]. NFIQ 2.0 (in development) [1], a standard open source quality assessment tool by NIST, uses a concatenation of multiple fingerprint features, trained with a supervised classifier. Motivated by this framework of NFIQ 2.0, we design a set of fingerprint features as candidate measures for quality estimation in latent fingerprints. Five sets of fingerprint features are as follows: (i) ridge quality [24] is based on the connectivity of the ridge flow with respect to its neighbourhood, (ii) spatial domain quality [7] computes the ridge clarity as a function of the principal Eigen value of a 2D tensor, (iii) power spectrum [10] computes the log power spectral density of the Fourier response of the fingerprint image, (iv) Gabor response approach [13] calculates the standard deviation of the responses of a filter of Gabor bank, and (v) DSIFT approach [23] computes the Dense SIFT features from predefined keypoints on the fingerprint image. Table 3 summarizes the parameters of the features used. A supervised neural network based classifier is employed to learn a qual-

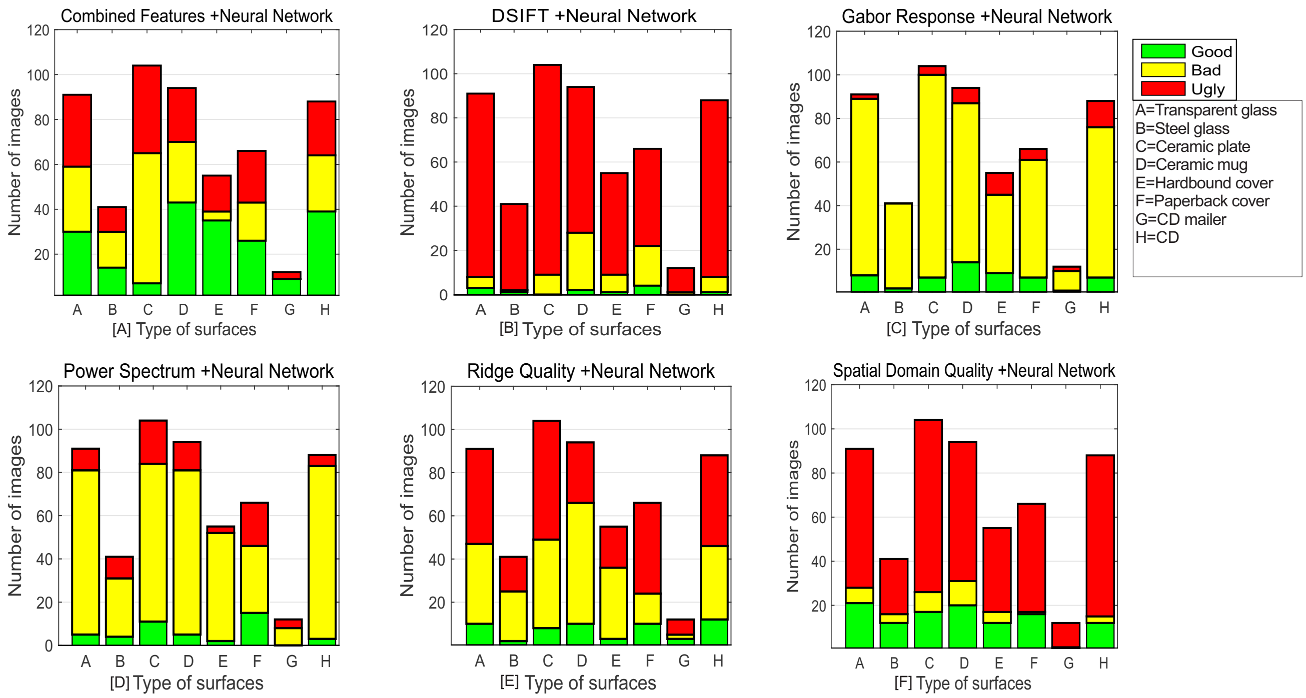

Figure 3. Bar plots showing distribution of fingerprint image quality for various surfaces using [A] the concatenated set of features [B], [C], [D], [E], and [F]. [B] the DSIFT feature [23]. [C] Gabor response feature [13]. [D] power spectrum feature [10]. [E] the ridge quality feature [24]. [F] spatial domain feature [7].

Table 3. The set of all features used in this research to compute the quality of latent fingerprints lifted from various surfaces.

Paper	Feature	Size	Parameters
Yoon *et al*. [24]	Ridge Quality ($Q_R^{(k)}$)	614400	k = 6, block = (32×32), $T_\theta = \frac{\pi}{10}$, $T_f = 3$
Chen *et al*. [7]	Spatial Domain Quality (Q_s, k_i)	2304	block = (32×32), q = 1
Guan *et al*. [10]	Power Spectrum (POW)	100	$\theta = [0, \ldots, 180]$, $\rho = [0, \ldots, 0.5]$ cycles/pixels
Olsen *et al*. [13]	Gabor Response (G_{std})	614400	Orientation $\theta = [0, 45, 90, 135]$
VLFEAT [23]	Keypoint (DSIFT)	115072	step = 24, size = 24, binSize = 8, magnif = 3

ity predictor from the input features. The latent fingerprints are classified into three quality labels: $\{Good, Bad, Ugly\}$. The NIST SD-27 database [5] has the ground truth quality labels annotated by forensic experts and these labelled latent fingerprint images are used to train the neural network architecture. Five neural networks are trained, one for each group of features and a final sixth neural network is trained for the concatenation of all the features. The trained classifier is then used to predict quality labels of the images pertaining to the proposed database. The distribution of fingerprint image qualities for each surface, using each feature, is shown in Figure 3. The important observations drawn from the quality analysis are as follows:

- It can be observed from Figure 3[A] that out of the total 551 latent fingerprints, 203 are classified as good quality (37%), 176 are labelled as bad quality (32%), and the remaining 172 are ugly quality fingerprints (31%). The overall quality of latent fingerprints in the database is poor, suggesting the challenging nature of the database.

- The neural network model learnt on the combination of all the features is able to provide a better quality distribution of fingerprints, rather than using individual features.

- From Figure 3[A], it can be observed that better quality prints are captured from surfaces such as ceramic mug, hardbound cover, and compact disc. Ceramic plate and transparent glass capture poor quality latent fingerprints.

4. Matching Performance

Latent fingerprint minutiae extraction and matching is a relatively open research problem that needs attention [17]. It is to be noted that there is no standard latent fingerprint matching SDK or publicly available automated system, which can be used to show the performance of latent fingerprint on our database. A survey of existing latent fingerprint matching algorithm in the literature shows that local Minutiae Cylinder Code (MCC) [6, 8] descriptor based matching provides state-of-the-art results [14]. Thus, in this research, latent fingerprint identification experiments are performed using MCC descriptor based matching. First, the minutiae are extracted using VeriFinger SDK 6.0 [2] and their corresponding MCC descriptors are then extracted for matching. To improve the performance of MCC descriptor based matching, the results are fused at decision level (OR fusion [15]) with the results of a Commercial-off-the-Shelf (COTS) system[2].

The aim of matching experiment is to study the surface-wise performance of latent fingerprints against the live-scan gallery images. Figure 4 shows the performance comparison of latent fingerprint lifted from different surfaces in the database. As observed in the quality distribution in Figure 3[A], ceramic mug provides the highest number of good quality images and hence the latent fingerprints lifted from ceramic mug surface provides the best matching performance (observed in Figure 4). However, it is interesting that even though latent fingerprints lifted from compact disc surface has a larger amount of *good* quality images, it is one of the lowest performing surfaces. This can be attributed to the fact that most of the quality estimation algorithms are ridge orientation and ridge structure based on; whereas matching is performed using minutiae. Thus, it can be safely concluded that, although the ridge structure of latent fingerprints lifted from compact disc surface is good, minutiae extraction fares poorly due to the glossy, reflective nature of the background.

Figure 5 shows the result for the quality model which is learnt on the combined feature set (Figure 3 [A]). For all the surfaces except hardbound cover images, the performance of *good* quality images is better than *bad* and *ugly* quality images. Hardbound covers produce maximum variations and noise in the background due to the presence of text and other structured noise. It is observed that the background noise contributes to spurious minutiae extraction, leading to poor matching performance.

[2]This COTS system is fine-tuned for tenprint matching.

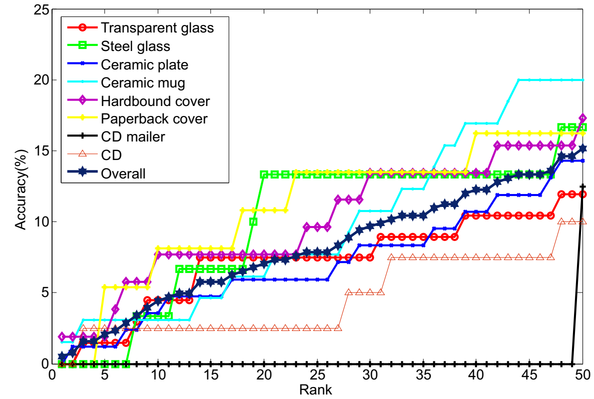

Figure 4. CMC curves showing the performance comparison of latent prints lifted from the eight surfaces. (Figure best viewed in color).

5. Conclusion

In this paper, we present a multi-surface latent fingerprint database and perform analysis based on quality and matching performance. To promote research in this problem, the multi-surface latent fingerprint database consisting of 551 latent fingerprints lifted from eight different surfaces is made available to the research community. Surface-wise quality analysis and identification experiments highlight some surface specific problems in latent fingerprint matching. We believe that the availability of this database can instigate research in this important problem.

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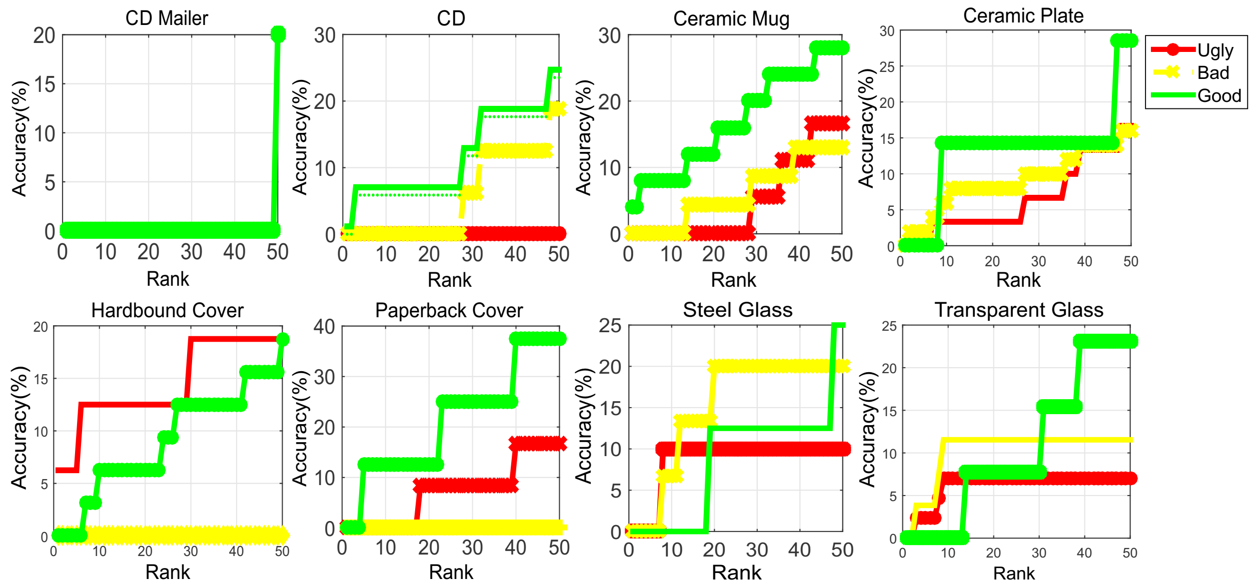

Figure 5. Cumulative match score curves showing the rank-50 identification accuracy of combined feature set with neural network classifier. The CMC curves show the performance comparison of the different quality latent prints in each surface. (from left to right) Top row: CD mailer, CD, ceramic mug, and ceramic plate. Second row: Hardbound cover, paperback cover, steel glass, and transparent glass. (Figure best viewed in color).

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