Latent Fingerprint Matching

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Abstract

Latent fingerprint comparison evidences are used in the court of law for more than 100 years. Manual matching of latent fingerprints is challenged by subjectivity and inconsistency in terms of results and is not scalable for large scale applications. Automating the process of latent fingerprint matching will practically equip forensic examiners in criminal investigation. However, a "lights-out" automated latent fingerprint matching system is still nascent from being used in a real time environment. Several research challenges in the development of an automated matching system are identified as: (1) lack of public latent fingerprint databases available for research, (2) low information content and partial fingerprint availability in latent fingerprints, (3) presence of background noise and non-linear ridge distortion in latent fingerprints, and (4) need of an established scientific procedure for matching latent fingerprints. A comprehensive survey in the growth of latent fingerprint matching, from a computational and algorithms perspective, is provided in this report. The whole process of automated latent fingerprint matching is divided into five definite stages and the research gaps in each of the stages are individually analyzed. Also, the limitations in manual matching of latent fingerprints are studied to gain insights as well as to set a baseline for an automated system. The major discussions in this survey include: (1) encourage researchers to create and establish results in public latent fingerprint databases, (2) to focus on the individual stages of a latent fingerprint matching system and approach them independently, and (3) explore the scope for using some non-standard fingerprint features, when minutiae extraction becomes challenging.

Index Terms

Automated latent fingerprint matching, ACE-V methodology, survey, IAFIS.

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I. Introduction

Fingerprint is a commercially successful biometric utilized for human identification. In 2012, the market of automated fingerprint identification systems and related technologies accounted for the greatest share of the global biometrics market and is forecasted to continue to be the main source of overall market revenues from 2010 to 2015 [2]. With growing demands for reliable personal authentication, supported by the recent advancements in technology and data handling capacity, fingerprints are extensively used in many civil, law enforcement and forensic applications such as access control systems, transaction systems, cross-border security, and crime scene analysis. Civil applications such as Indian government's Aadhaar project, Department of Homeland Security's US-VISIT program, and the UK Border Agency use rolled (nail-to-nail information) or slap (dap or flat) fingerprints for authentication. Such fingerprints are used in recent large-scale applications. Extensive research has been done in fingerprints captured using these methods [52], [53], [55], [86]. As shown in Fig. 1(a)-(d), these fingerprints can be captured using offline (inked) or live-scan methods. On the other hand, forensic applications employ latent fingerprints, as shown in Fig. 1(e), for crime scene investigation. Latent fingerprints are deposited when the sweat, amino acids, proteins, and natural secretions present in the surface of the skin come in contact with an external surface. These fingerprints are not directly visible to human eyes and after lifting using special procedures, they are used as evidences in court proceeding. As shown in Fig. 2, latent fingerprints vary a lot in quality and information content depending on the nature of the skin and surface.

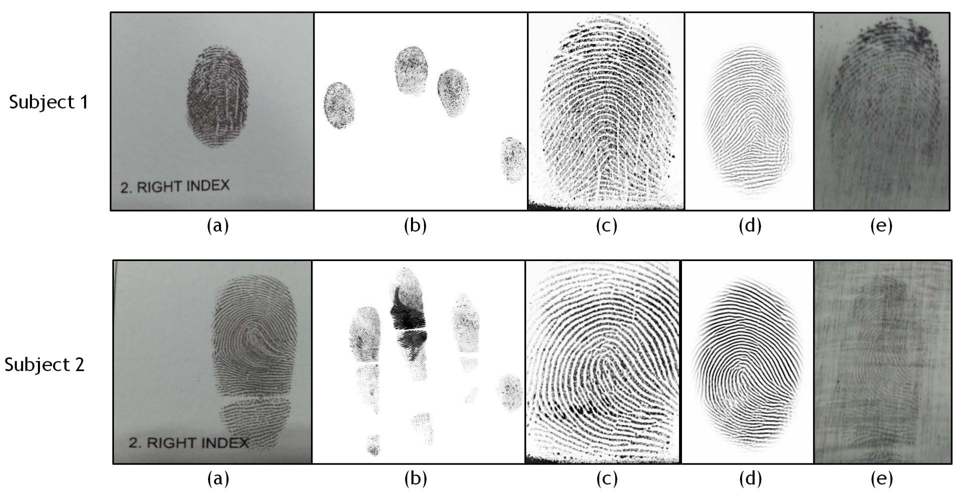


Fig. 1. Fingerprints showing high inter-class and intra-class variations. The right index finger is captured from two different subjects using different capture methods. (a) Inked fingerprint, (b)-(d) Live scan fingerprints: (b) CrossMatch sensor, (c) Secugen Hamster IV sensor, (d) Lumidigm multi-spectral sensor, and (e) Latent fingerprint lifted using black powder dusting method.

Fig. 3 demonstrates a stepwise procedure observed for analyzing latent fingerprints obtained from a crime scene. The latent fingerprints lifted from a crime scene are manually annotated by forensic experts. An Integrated Automated Fingerprint Identification System (IAFIS) matches the annotated fingerprints and provides the list of *top-K* probable matches. The list is then manually verified by a forensic expert to make individualization, if available. This procedure involves manual intervention at many stages which are time consuming, laborious, and subjective to variations. To reduce manual

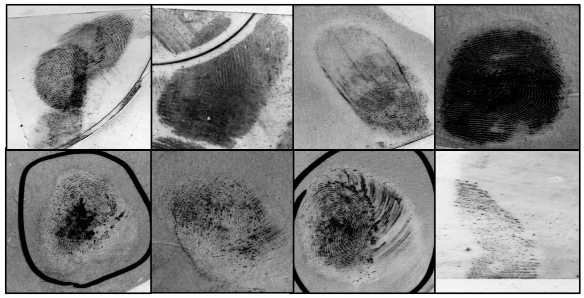


Fig. 2. Some sample latent fingerprint images from the ELFT-EFS database [4].

intervention, automating the entire pipeline of latent fingerprint matching would be effective. Many hyped visuals of a fully automated crime scene investigation are shown in some latest science fiction movies such as Jack Reacher, The Dark Knight Rises, Mission Impossible: The Ghost Protocol and television shows such as CSI. However, the development of this technology, its accuracy and speed, as shown in these movies are still farfetched and fictitious, though that would be the ultimate goal to achieve.

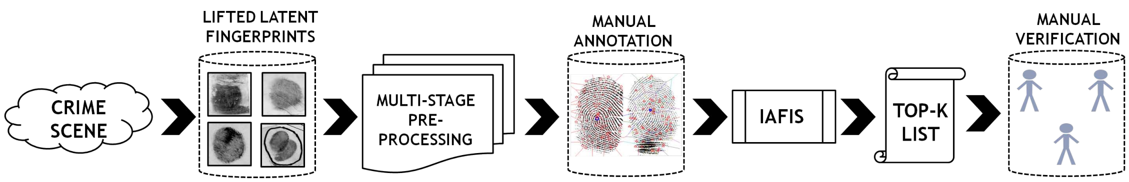


Fig. 3. A stepwise, semi-automated procedure for analyzing latent fingerprints obtained from a crime scene. The dotted cylinders represent the human intervention in the latent fingerprint identification process.

To encourage the growth in technology and research in automated latent fingerprint matching, FBI's CJIS (Criminal Justice Information Services) division awards the title "The Hit of the Year" since 2007. This award is given to the best solved case by IAFIS using latent fingerprints [8]. This award highlights the utility of latent fingerprints in crime scene investigation and the advancement in latent fingerprint matching technology. Some of the recent recipients of this award are listed below:

- The 2012 "The Hit of the Year" [7] was awarded for solving a 33-year old case of the brutal murder of Carroll Bonnet. In 1969, the collected evidences (latent fingerprints and palmprints) were not enough to make a positive identification due to the lack of automated biometric technologies and the unavailability of large background fingerprint databases. However in 2009, the same evidences were sent to FBI's IAFIS for matching and within five hours IAFIS returned a set of possible suspects. Upon manual inspection of the suspects, the criminal was identified and found guilty, exactly 33 years after the crime occurred.
- The 2010 "The Hit of the Year" [6] recognized solving of the 1972 San Deigo case, where a man was stabbed more than 50 times and murdered. In 2008, the case was reopened and the latent fingerprints lifted from the crime scene were matched by FBI's IAFIS system. The system returned top 20 matches and upon further manual investigation the latent fingerprint was correctly individualized to the murderer. The convict pleaded guilty and once again latent fingerprint along with the murderer's DNA served as major evidence in solving a cold murder

case.

It is to be noted that, at many places, latent fingerprint matching is still performed in a manual or semi-automated environment. Latent examiners are expected to analyze large number of latent fingerprints in a short time span. The constraints on time and efficiency lead to inconsistent and sometimes erroneous results by human experts. These mistakes are compiled in the Innocence project [14], [26] and some case studies are discussed below:

- Shirley Mckie fingerprint case [3] was one of the high profile cases of false accusation. Shirley Mckie, a Scottish police officer, was wrongly charged with perjury after her fingerprints were found at the murder scene of Marion Ross. David Asbury was the prime suspect as his fingerprints were found on a gift tag in Ross's home. However four expert examiners provided testimony for Shirley's latent fingerprint match and Shirley was arrested. The only evidence that was held against her was the latent fingerprint and after months of imprisonment she was released without a formal apology.
- Another case happened with the Madrid bombings in 2004, when Brandon Mayfield, an American lawyer was wrongly arrested [13]. The latent fingerprints obtained from the bomb site were matched using an FBI's system and it returned a match with Brandon Mayfield. After two months of incorrect allegation and 14 days of imprisonment, the court released the lawyer declaring his innocence while FBI announced a public apology. The court of law documented that "The incorrect arrest sprang from an erroneous match of latent fingerprint by FBI's supercomputer system" [13].

The above case studies show that latent fingerprints could be used as informative evidence in the court of law. However, an automated matching technology for latent fingerprint is still nascent to be used in real time environments. With growing needs and applications of latent fingerprint matching, there are several challenges faced by the forensic and research community for developing automated systems. Some of these research challenges are tabulated in Table I. The broader challenge is to develop a definite scientific procedure, with minimum subjectivity, to match latent fingerprints. However, major challenges for developing an automated system are at computational and algorithmic level where we attempt to reproduce the efficiency of human visual system, human knowledge and human contextual decision making capabilities.

A. Research Contribution

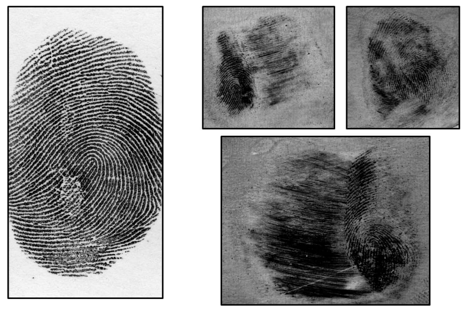
Consider a human expert matching the latent fingerprint with the exemplar fingerprints as shown in Fig. 5. Only 2 exemplar fingerprints, (a) and (e), are true matches for the latent while the remaining three are false matches. During this match, forensic experts provide subjective conclusions and tend to commit errors in feature extraction and matching due to the visually observable challenges like partial and noisy information. In a practical scenario, when the number of latent fingerprints and the background exemplar fingerprints are high, manual matching is not scalable both in terms of the time taken and performance obtained. Automated "lights-out" latent fingerprint matching is still in its naive stage and has received a lot of research attention in the last few years. It is very important to understand the difficulties involved in latent fingerprint matching in providing

Type	Challenges	Description
Resource	Lack of experts	Latent fingerprint matching requires trained forensic experts to perform error free matching. Compared to the enormous number of crime scene fingerprints obtained, there is a lack of skilled experts who are authorized to perform the comparison.
	Lack of databases	Research in automated latent fingerprint matching is challenged by the lack of publicly available latent fingerprint database. Due to the enormous challenges involved in creating a latent fingerprint database (or sharing an actual crime scene database), researchers do not have a common database to test their algorithms.
Latent fingerprint image (Computational)	Availability of partial latent fingerprint ridge information	As the entire distal phalanx bone region does not come in contact with the object, the entire fingerprint will not be deposited on the surface. Refer to Fig. 4(a).
	Poor quality of the available ridge information	The available ridge information would be smudgy and imperfect as shown in Fig. 4(b). This may be because of the uneven pressure with which the person holds the object or because of the loss of information while lifting the fingerprint.
	Presence of background noise	The latent fingerprint could be lifted from any surface that comes in contact with the hand, hence the amount of distinguishable ridge information depends on the background surface characteristics such as type, material, and texture. These constitute the background noise of the latent fingerprint.
	Non linear distortion in ridge information	The surface from which the latent fingerprint is lifted need not be always flat. Hence, with respect to the shape of the surface, the ridge information in the fingerprint gets distorted or warped in a non-linear manner, as shown Fig. 4(c).
Procedure	Lack of established scientific procedure in matching latent fingerprints	Enough research has not been done in devising a standard scientific procedure for matching latent fingerprints. The immediate consequence, of which, allows a latent fingerprint expert to use his subjectivity and experience while matching latent fingerprints.

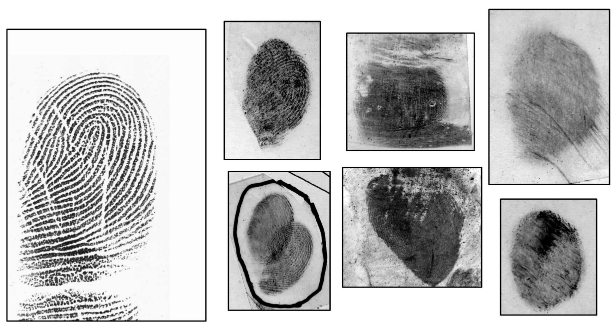
TABLE I
RESEARCH CHALLENGES IN AUTOMATED LATENT FINGERPRINT MATCHING.

a perspective of the state-of-art. This comprehensive report is focused upon the computational and algorithmic perspectives of latent fingerprint matching. A detailed analysis of literature is performed to study the research gaps of automated latent fingerprint matching. An understanding of the human expert way of matching latent fingerprints is provided to gain insights as well as to set a baseline for automated systems. Various technological and philosophical concerns involved in latent fingerprint

(a) Partial availability of latent fingerprint ridge information.



(b) Poor quality of ridges, smudges and presence of dusting noise.



(c) Presence of non linear distortion in latent fingerprint ridges.

Fig. 4. Challenges in latent fingerprint matching.

matching are also addressed in this survey.

The remaining report is organized as follows - Section II discusses about the human standards for matching latent fingerprint matching and its analysis while section III describes the various aspects of an automated latent fingerprint matching system. Section IV explains the importance and the procedure for calculating the evidential value while processing latent fingerprints. Section V discusses some publicly available latent fingerprint databases available for research, provides the baseline identification results and other experimental results on latent fingerprint matching.

II. ACE-V Method For Manual Latent Fingerprint Matching

It is important to understand how humans examine and match latent fingerprints as it provides insight for building an automated system. Human examination of latent fingerprint is performed using the ACE-V (Analyis, Comparison, Evaluation, Verification) procedure [19]. ACE-V is a structured, systematic guideline for matching friction ridge impressions. There are four sequential phases in ACE-V methodology: Analysis, Comparison, Evaluation, and Verification, as shown in Fig. 6. After every step, the knowledge gained thus far is applied in the execution of further stages. An overview

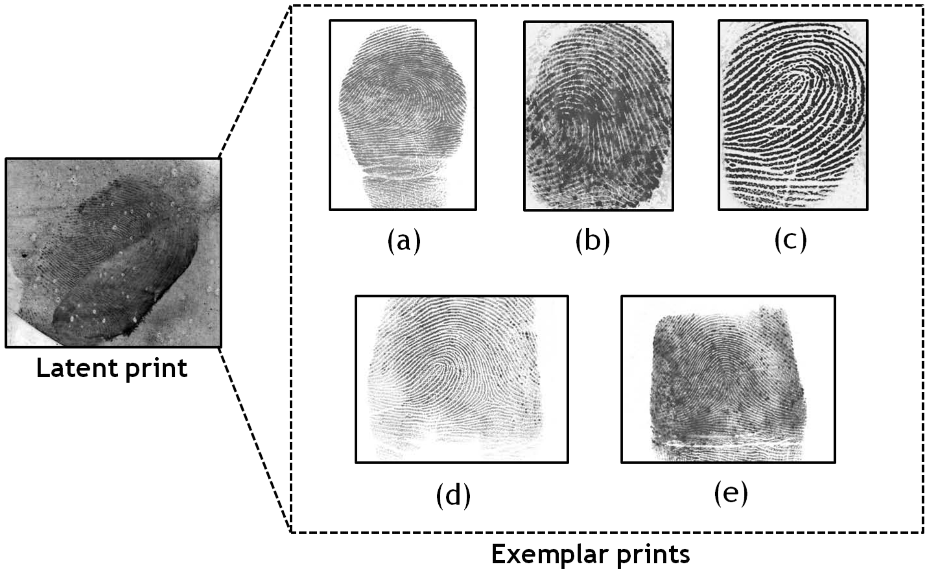


Fig. 5. An example illustrating the challenge of latent fingerprints. A sample exemplar fingerprint along with a pool of latent fingerprints (a)-(e) is shown. Of these five latent fingerprints, only two are mated with the exemplar fingerprint, while the remaining three are false matches.

of the procedure is explained below:

1) **Analysis:** An in-depth friction ridge analysis is performed on a digitally scanned latent fingerprint. The latent fingerprint is studied for different anatomical aspects, deposition pressure, distortion due to pressure, and the substrate matrix. Each fingerprint is assigned a label during this stage - Value for Individualization (VID), Value for Exclusion (VEO) only, and No Value (NV). The features of latent fingerprints are marked during this stage.
2) **Comparison:** The comparison is a process where visual comparative measurements are made between the latent and the exemplar fingerprints. The comparison is made in a sequential, spatial and configurative manner where marked features are compared in the order of Level-1, Level-2, and Level-3 features. Both similarity and dissimilarity comparison analysis are made and a score value for comparison is assigned. As much as possible, the examiner should perform comparison blindly without any subjective or contextual measurements.
3) **Evaluation:** Based on the comparison, one of the three decisions is taken during the evaluation stage: Individualization, Exclusion, or Inconclusive. The evaluation stage mostly overlaps with comparison stage when the ridges clarity are very clear (individualization decision) or very poor (exclusion decision). Evaluation stage plays a key role in making inconclusive decisions.
4) **Verification:** Verification is a form of peer review. During verification, the entire process of Analysis, Comparison, and Evaluation is verified by another examiner to increase the reliability of the match.

The manual annotation of latent fingerprints and matching is arduous and is not scalable. Given the constraint that latent examiners have to match large number of latent fingerprints in a limited amount of time, a huge pressure is stressed upon the latent examiners. To speed up the process of matching, latent experts tend to use their subjectivity and experience to bypass certain steps, thus allowing the credibility of latent fingerprint matching to be questioned in the court of law [37], [84]. Cole [25]

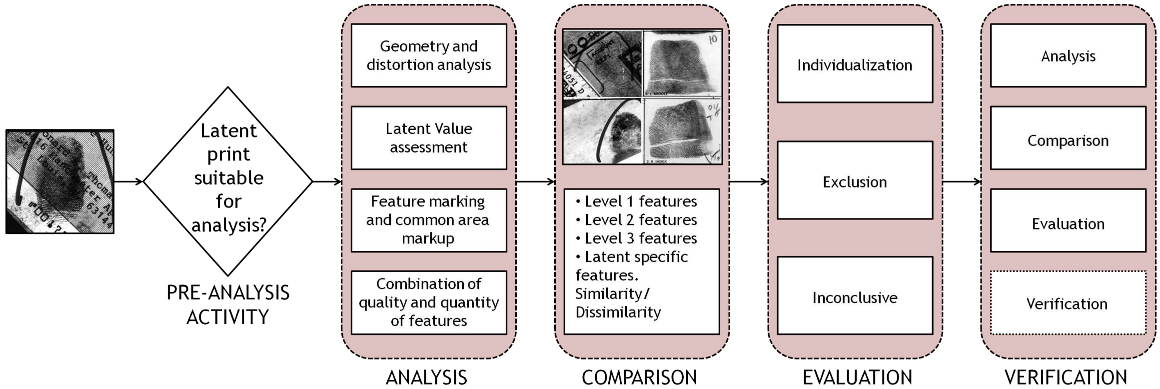


Fig. 6. ACE-V methodology for manual matching of latent fingerprint.

in 1999, brought this to limelight when he put forth the discussion that many Latent Finger Print Examiners (LFPE) argue about the lack of a "scientific" approach for latent fingerprint matching. Cole raised an issue of what could constitute a "scientific" method and provided few directions for contributing towards forensic science. Cole [26], in 2005 gave a more comprehensive account of the issues and errors in using latent fingerprint as an evidence in the court of law. Mnookin [58] in 2008, in his suggestive report, laid down the confessions of an actual latent fingerprint examiner and strongly questioned the existence of a scientific basis for latent fingerprint comparison. This report emphasized the criticality of latent fingerprint matching in forensic science and also attracted researchers to address the problem of automatic latent fingerprint matching.

In 2009, the Scientific Working Group on Friction Ridge Analysis, Study and Technology (SWG-FAST) created a standard for documenting latent fingerprint matching using ACE-V method [17]. According to the standards, only the trained latent fingerprint examiners could perform latent fingerprint matching. Every single match stage had to be documented in a specific format, either during the evaluation or soon after it has been done. ACE-V methodology is generally accepted as a scientific standard for comparing latent fingerprints as it tests the hypothesis of the decision made by the comparison and verification process. In 2005, a Committee to Define Features for Fingerprint Systems (CDEFFS) [16] was formed as part of the National Institute of Standards and Technology (NIST) to define standards, quantifiable methods, and regulations for characterizing the information content of frictional ridge image. By the end of 2011, CDEFFS proposed Extended Feature Set (EFS) for fingerprints and included them in the ANSI/NIST ITL-1 2011 type-9 record. The Evaluation of Latent Fingerprint Technology (ELFT) using EFS (Evaluation #1) was released in 2011, which demonstrated the performance of minutiae and other features on latent fingerprints. EFS was also presented as the basis for Latent Inter-operability Transmission Specifications (LITS) [77]. The evaluation results are still in its preliminary stage and a huge research focus is set towards designing new and extended features for latent fingerprint matching.

A. *Study on Human Performance*

To evaluate the human performance for latent fingerprint matching and to quantify the error during manual matching, Ullery et al. [79], [80] conducted two different studies in 2011 and 2012 respectively. In the first research, Ullery et al. [79] studied the accuracy and reliability of an expert's decision in latent fingerprint analysis. Three key objectives constituted the study:

- To study the frequency of error: Error is quantified in terms of both false positive rate and false negative rate, as both these false classifications are costly during a latent-exemplar match.
- To study the consensus among examiners: While performing the same latent-exemplar match, if different examiners tend to provide different results, the reliability of such a decision would be low.
- To study the factors affecting the decision of latent examiners that contribute towards variability in results.

A total of 169 latent print examiners, having a median experience of 10 years and with 83% of them certified as latent examiners, participated in the study. The database included 356 latent fingerprints from 165 distinct fingers and 484 exemplars. 744 distinct latent-exemplar image pairs were formed having 520 mated and 224 non-mated pairs. Each of the examiners was randomly assigned 100 image pairs out of the total pool of 744 pairs. It was observed from these experiments that the true negative rate was greater than the true positive rate in manual examination. 85% examiners made at least one false negative error with a false negative rate of 7.5% and a small false positive rate of 0.1%. By independently verifying the results obtained from other examiners, all the false positive matches and most of the false negative matches were removed. Also, the examiners frequently differed in deciding whether the fingerprints had enough information for reaching a conclusion or not. In a recent study [80] in 2012, the same authors studied the repeatability and reproducibility of decisions made by latent examiners. Generally latent fingerprint examiners use their expertise rather than a quantitative standard to analyze latent fingerprints. It is very useful and interesting to study if latent examiners can repeat their own results independently (intra-examiner study quantifying repeatability) and also if an examiner's results can be reproduced by other examiners (inter-examiner study quantifying reproducibility). A total of 72 examiners were reassigned 25 image pairs after an interval of approximately seven months. The repeatability of comparison decisions was 90% for mated pairs and 85.9% for non-mated pairs. In essence, for a true positive match, an examiner can repeat his own decision only 90% of the times. However, most of the inconsistencies in examination resulted in inconclusive decisions. Also, the inter-examiner study showed that examiners were able to reproduce other's results only 81% of the time, with only 52% for "difficult" types of fingerprints. Similar conclusions were drawn by Dror et al. [29], when they conducted studies for intra and inter consistency among examiners. To remove bias, they used only latent examiners for their studies rather than forensics or psychology students. Statistically, the intra-examiner consistency provided more insights to the subjectivity of an examiner. They also studied about the variation in the analysis by a latent examiner under the context of target comparison. Examiners were allowed to analyze and mark feature (minutiae) points independently, without showing any target matching fingerprints. When the examiners were shown with target full fingerprints and asked to mark minutiae as a pair, a variation of about (2.6 ± 3.5) minutiae was found in manual marking. The context of target fingerprint was a very influencing factor during the analysis phase of ACE-V method. A simple train tool was suggested to avoid the problem of inconsistency among examiners. The tool could provide a qualitative or quantitative feedback based on the correctness of the examiner with respect to the other examiners. This feedback could be used by an examiner to attune their thresholds to remain consistent with other examiners.

The main disadvantages of the aforementioned studies were that the examiners were conscious of the motive of experiments and also there were no time constraints forced for matching. Some conclusions derived from the studies performed on human capabilities in matching latent fingerprints are summarized below:

- Humans set hard thresholds and are very cautious about making a false positive match. Thus, in manual matching very low false positive rates and high true negative rates can be observed.
- Human examination of latent fingerprints is prone to inconsistencies and errors. A forensic expert is allowed to use his/her experience during matching thereby making the ACE-V standard more flexible.
- Human examination is not scalable for large scale latent fingerprint matching applications as it is an arduous and time taking process.

III. Automated Latent Fingerprint Recognition System

The primary aim of an automated latent fingerprint recognition system is to minimize the human intervention as much as possible. An automated matching system will be deterministic and avoid subjective inconsistency. It also optimizes the time required for comparison. For example, the current FBI's IAFIS system takes an average time of 1 hour, 53 minutes and 12 seconds for matching a latent fingerprint image against the enrolled gallery of 73.1 million fingerprints [5]. Therefore, an automated latent fingerprint matching system is expected to provide quicker, better and more deterministic results than manual matching. As shown in Fig. 7, the overall process of an automated matching system can be broken into a set of sequential stages: (1) latent fingerprint capture or lifting, (2) latent fingerprint segmentation or ROI extraction, (3) latent fingerprint quality assessment and enhancement, (4) feature extraction, and (5) matching. In a broader perspective, this overall process can be effectively classified into two groups: before feature extraction and after feature extraction. Feature extraction plays the pivotal role in representing and matching latent fingerprints. This section explains in detail the literature of different stages involved in automated latent fingerprint matching. To better understand about the origin of fingerprints and its ridge structures, a small description of fingerprint formation is discussed in Appendix A.

A. Latent Fingerprint Capture

Latent fingerprint detection, lifting and capture are some of the most exhaustively studied topics in latent fingerprint matching. Advancements in chemical and physical science has solved multiple challenges in latent fingerprint lifting [51]. There are a variety of techniques used for latent fingerprint lifting including powder based [75], solvent based, UV based, ultra sound based, fuming based, electromagnetic based techniques, and contact-less fingerprint lifting [11]. The specific method to be used depends on the material and geometry of the surface from which the latent fingerprints are lifted, the expertise of the examiner and the environment. A small study on different methods employed on

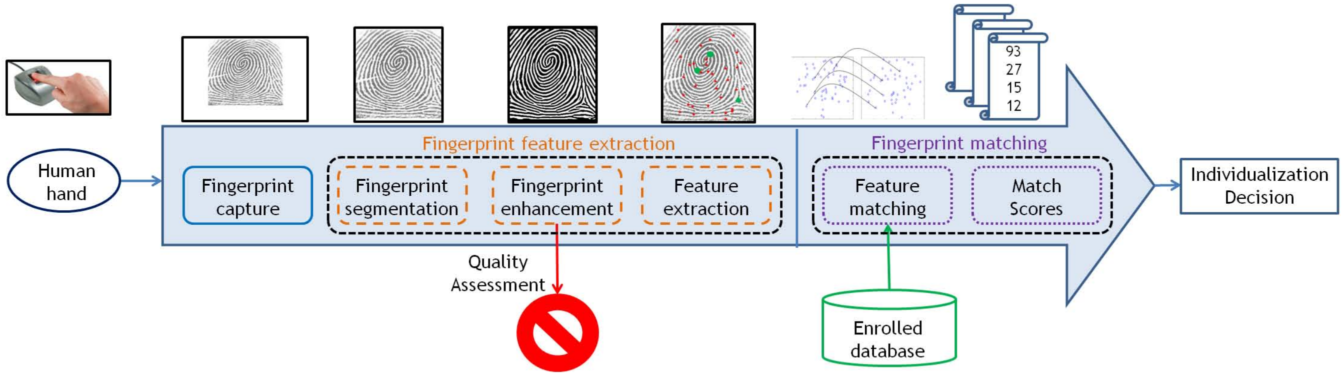


Fig. 7. The overall schema of an automated latent fingerprint matching system.

Fig. 8. Latent fingerprint lifted using different chemical techniques. Images are obtained from different source in Internet.

various background surfaces is shown in [36], [85]. Sample latent fingerprints lifted using different techniques are shown in Fig. 8. The forensic examiner might conduct some preliminary tests such as magnifying glasses and UV light to determine if a latent fingerprint is available at a particular location. Generally it is left to the examiner on the crime scene to choose from where to lift the latent fingerprint and which method to employ. Lee and Gaensslen [53] and Thompson [78] showed a detailed procedure followed by forensic experts for lifting fingerprints from different surfaces. Some of the prime challenges encountered in common latent fingerprint lifting techniques is:

- Smudges and strokes introduced by chemical reagents or brush adds to the noise and information loss during latent fingerprint lifting.
- The surface from which the latent fingerprint is lifted, the contact pressure and the contact duration of the finger with the surface, and contamination of finger skin with oil and sweat will vary the quality of fingerprints [56].
- The tape method used to lift fingerprints introduces non-linear distortion in the ridge flow of fingerprints.
- Sometimes a small mistake committed by a forensic expert leads to the deletion of latent fingerprint before it is lifted. This may lead to some serious failure to gather evidence from a crime scene.

To overcome the above mentioned challenges, researchers currently focus on contact-less latent fingerprint lifting techniques. Hildebrandt et al. [42] proposed a highly useful application of contact-less latent fingerprint lifting in airport luggage handling. Kiltz et al. [87], in 2012, presented a recent survey of the various contact-less latent fingerprint lifting methods and it's challenges. An analysis of various sensor techniques, spectroscopy and multi sensor fusion approaches were studied and seven prime challenges in contact less latent fingerprint lifting were identified and summarized below:

1) Need for the integration of different methods in lifting
2) Determination of sensor parameters
3) Sensor types for different surfaces
4) Non-planar surface
5) Influence of dust and dirt
6) Age detection of fingerprints and separation of overlapping fingerprints
7) Extension of benchmarking scheme.

B. Latent Fingerprint Segmentation

Fingerprint segmentation involves separating foreground latent fingerprint from any kind of background noise. Latent fingerprint segmentation is a challenging task due to the lack of discrimination in estimating the relevant information and ill-posed boundary of the foreground. Some examples in Fig. 9 visually describe the challenges in latent fingerprint segmentation. As observed, there is an ill-defined boundary between the foreground and background. However, in the context of latent fingerprints, the definition of segmentation can be perceived in different ways. Latent fingerprint segmentation may be defined as marking out only the outline boundary, as shown in Fig. 10(b), or marking out the boundary including the smudges and structured noises inside the boundary, as shown in Fig. 10(c). Since segmentation is the first step in latent fingerprint matching, the motive of segmentation should be to mark all the foreground regions accurately, while allowing as minimum background as possible.

Even though very few researchers have worked on latent fingerprint segmentation, there are some well understood and accepted challenges.

- Latent fingerprints can be lifted from a variety of surfaces including glass, wood, paper, and metal. The extensive list of surfaces from where latent fingerprints can be lifted vary significantly in textures, patterns, and colors as shown in Fig. 9. Therefore, background modeling or prediction is a challenging task.
- Due to the variation in pressure applied while depositing and errors while lifting, the ridge information present in a lifted latent fingerprint is generally of very poor quality and therefore assessing the quality of ridge patterns is also challenging.
- As shown in Fig. 11(a), two or more latent fingerprints are often overlapped during lifting. Estimating the orientation of the latent fingerprints independently and segmenting them is also a hard problem.
- As shown in Fig. 11(b), structured noise such as arch, lines, and characters very often resemble ridge patterns and pose a challenge in differentiating between ridge and non-ridge patterns.

Fig. 9. Example latent fingerprint images from NIST SD-27 visually demonstrating the tough nature of latent fingerprint segmentation. It is observed that the foreground ridge information and the background noise are highly intertwined and overlapped making it hard to segment the relevant information.

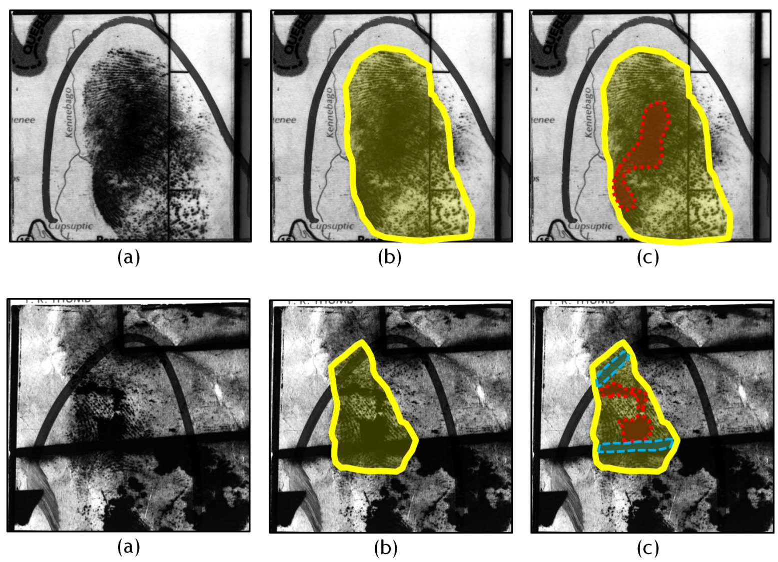
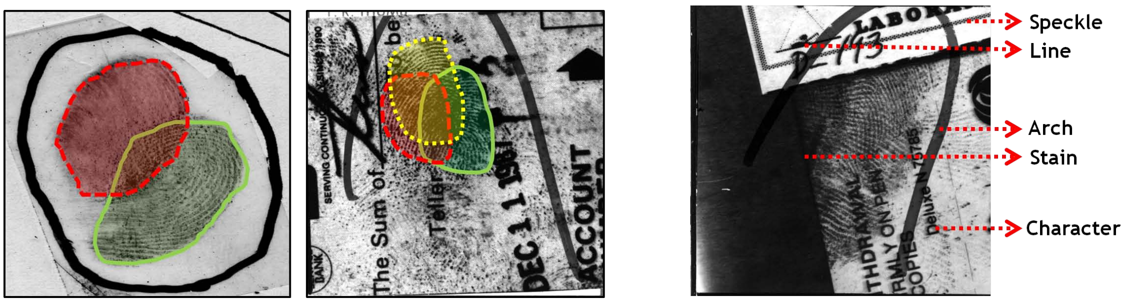


Fig. 10. Sample latent fingerprints demonstrating different ways of segmenting a latent fingerprint image. (a) original latent fingerprint image, (b) segmentation of the outline of the entire latent fingerprint, and (c) segmentation of the outline of latent fingerprint (yellow full lines) and marking the structured noise (blue dashed lines) and smudgy region (red dotted lines) overlapping with the print.

Karimi and Kuo [47] proposed the first automated approach of latent fingerprint segmentation in 2008. They computed the orientation and frequency components at local windows to estimate the regional uniformity property of the fingerprint ridge patterns. A reliability measure is computed using inter-ridge distance for segmenting the foreground image. The results were demonstrated using two images from the NIST SD-27 database [18]. In 2011, Short et al. [74] proposed a segmentation technique by preprocessing latent fingerprints and cross-correlating it with an ideal template of ridge patterns. Based on the correlation strength, the regions were classified as foreground and background. An Equal Error Rate (EER) of 33.8% was reported on the NIST SD-27 database. In 2012, Zhang et al. [91] identified six different patterns of structural noises that could be found in the background of a latent fingerprint - lines, arches, characters, stains, speckles, and others. The authors further proposed



(a) Overlapped latent fingerprints

(b) Structured noise

Fig. 11. Example latent fingerprint images from NIST SD-27 showcasing two specific challenges in latent fingerprint segmentation. (a) Overlapped fingerprints result in overlapped ridge information making it difficult to determine the ridge flow of either of the fingerprints, and (b) the presence of structured noise in latent fingerprint background that often resemble ridge like patterns.

a preliminary approach using total variation (TV-L1) model to remove the structured patterns and noise in the background. The model is made adaptive by dynamically adjusting the fidelity coefficient that separates the texture patterns of the foreground with the background. The proposed model was observed to perform efficiently for three sample images from the NIST SD-27 latent fingerprint database. The authors later in 2012, proposed a Directional Total Variational (DTV) model [92] which is a variant of TV-L2 model for identifying ridge patterns. The proposed DTV model is suitable for decomposing textures with orientation patterns. The extracted orientation vector controls the separation extent of foreground with background. The working of the proposed model is visually demonstrated using three sample images from NIST SD-27. More recently, Choi et al. [23] proposed a two step segmentation process using both orientation tensor and frequency tensor (local fourier analysis). The orientation tensor was applied to eliminate structured noise in the background while the local fourier analysis detected ridge like patterns in a local window. The final segmentation output was obtained by intersection of segmented masks obtained from the individual tensors. Experimental results showed the rank-1 identification accuracy of 16.28% on the NIST SD-27 database and 35.19% on the WVU database. It was observed that the algorithm failed to segment some low contrast latent fingerprints from the WVU database [65].

The problem of segmentation becomes even more challenging when there are more than one latent fingerprint impressions overlapping partially that need to be separated individually. In 2012, Zhao and Jain [93] proposed a model based approach for segmenting overlapping fingerprints using relaxation labelling algorithm. By mathematically modeling the fingerprint orientation field, the authors attempted to enhance the orientation of the overlapping fingerprints especially for low quality fingerprint images. Two different databases were created for experiments: an overlapping fingerprint database and a simulated latent fingerprint overlapping database. The ground truth orientation field of the overlapping fingerprints was manually marked by the experts and the results showed improvement for both the databases. This research work also pointed out the absence of a database with overlapping latent fingerprints to encourage further research in this area. Feng et al. [32], further improvised this approach for two specific cases: (i) the mated template fingerprint for one of the overlapping fingerprint is available and (ii) both of the overlapping fingerprints are from the same finger. Specific constraints were added to the constraint based relaxation labelling algorithm to address each of these cases specifically. Experiments were performed in two publicly available database: a simulated ten-print overlapping database and a latent fingerprint overlap database. The proposed algorithm approximately showed a rank-1 identification of 85% on latent fingerprint database and 96% on simulated database. Recently, Schott et al. [71] suggested the usage of a latent fingerprint aging feature called Binary Pixel to separate overlapping latent prints. Among the overlapping fingerprints, the age estimation assessed the sequence of latent fingerprint deposition, thereby differentiating the prints. Experimental results showed a success rate of 70%, irrespective of the initial age of either of the print.

An automated latent fingerprint segmentation system is still farfetched from being confidently used in an AFIS. Fig. 12 shows two sample latent fingerprint images along with its expected manual segmented outputs and the output from *nfseg* module of NBIS [12] and Choi et al.'s algorithm [23] (implemented by the authors). As it can be visually observed, one of the state-of-art algorithms for latent fingerprint segmentation misses out on valid foreground regions in many cases. This shows that there is a scope for further research and improvement in latent fingerprint segmentation. Also, there is no standard definition for the expected output of the segmentation stage in AFIS. As shown in Fig. 12, the segmentation can be perceived and performed in different ways. In future, a well justified and standard way of segmenting latent fingerprints should be defined such that automated algorithms can work towards that direction.

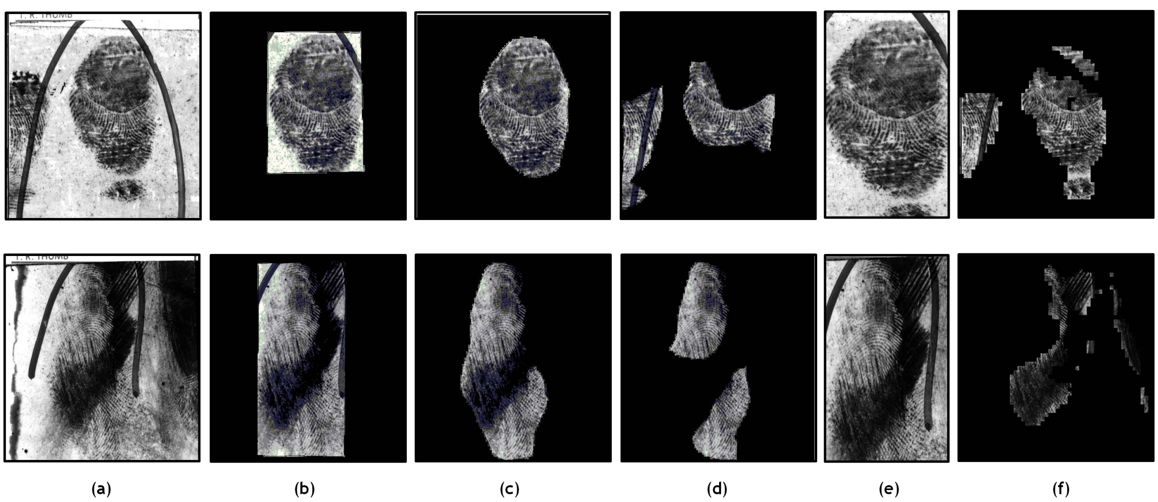


Fig. 12. Sample latent fingerprints from the NIST SD-27 fingerprint database [18] showing segmentation results. (a) Original latent fingerprint images, (b) manually segmented output with just a bounding box around the fingerprint region, (c) manually segmented output with exact boundary around the fingerprint region, (d) manually segmented output with only the useful ridge information rejecting all the smudgy and noisy (non-informative) regions, (e) segmented output from *nfseg* module of NBIS [12], and (f) segmented output from Choi et al. algorithm [23] (implemented by the authors).

C. Latent Fingerprint Quality Assessment and Enhancement

Latent fingerprint ridge flow enhancement is a very crucial and important process before feature extraction. The assessment process evaluates and the enhancement process improves the quality of a latent fingerprint. Given a segmented latent fingerprint, an information assessment has to be made to check if the segmented impression has minimum information to make a valid confident match.

Latent fingerprints that do not qualify for minimum information content should be discarded as FTE (Failure To Enrol) or FTR (Failure To Register) fingerprints [55] and they generally do not affect the performance accuracy of the matching system. Quality enhancement assists the feature extraction process by removing the noise and improving the clarity of a latent fingerprint image. Thus, latent fingerprint enhancement increases the confidence of the features to be extracted.

Very few researchers have worked on a quality assessment and improvement of latent fingerprints. Fig. 13 shows a few latent fingerprints enhanced using VeriFinger SDK 6.0, one of the popular commercial systems used for ten-print matching. It can be observed that the latent enhancement using VeriFinger fails because of the incorrect orientation field estimation of ridge patterns. Some of these general challenges associated with latent fingerprint quality enhancement are summarized below:

- The poor quality of ridges and the partial availability of fingerprints is a challenge for ridge quality assessment.
- Structured noise that resembles ridge patterns such as brush strokes, circular markings, and characters sometimes are enhanced better than the ridge information itself. Also, the ridge information is lost and noise is enhanced when the structured noise overlaps with ridge information.
- Segmentation error affects the performance of quality enhancement. Some contemplating textures in the background similar to ridge patterns are enhanced thereby distorting the actual fingerprint, as shown in Fig. 13.
- Parameterized enhancement algorithms face challenges in training or fine tuning their parameters as the environment from which latent fingerprints can be lifted is not limited.

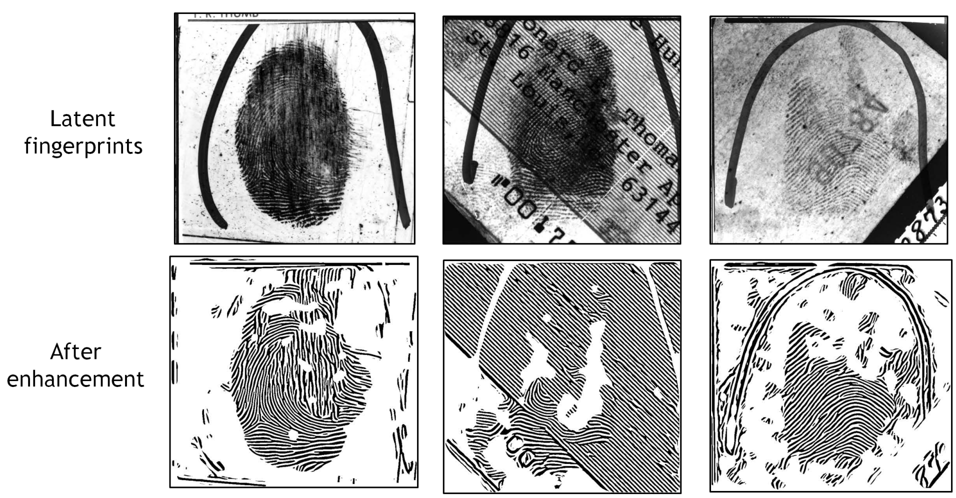


Fig. 13. Sample latent fingerprints from NIST SD-27 enhanced using VeriFinger SDK 6.0.

Quality Assessment: Hicklin [39] in 2007 performed the first study on latent fingerprint quality assessment by comparing the confidence of various levels of fingerprint features towards quality estimation with the results from human experts. The confidence of matching latent fingerprints using level-1 features was much higher than using level-2 or level-3 features. In 2011, NIST provided the complete set of experimental features for NFIQ 2.0 [41], which is the quality metric for latent fingerprints. Olsen et al. [61] in 2012 suggested the use of Gabor filters as a candidate quality feature along with other features for NFIQ 2.0. However, they did not publish the results on latent fingerprints and hence its effectiveness in latent fingerprints is still unknown. Recently, Yoon et al. [90] provided a metric for latent fingerprint quality assessment. Following the ACE-V standard for deciding the value of latent fingerprints at analysis level, the authors performed a local ridge analysis to analyze the clarity of latent fingerprints. The ridge clarity maps, combined with the number of minutiae extracted, acted as a good matching dependent predictor of quality latent fingerprints. Using this quality measure, a two-class problem was formulated to estimate if the latent fingerprint is a VID (Value of Individualization) or not-VID. On a combined database of NIST SD-27 [18] and WVU database [27] with manually extracted minutiae, the authors reported a classification accuracy of 88%.

Quality Enhancement: In 2010, Yoon et al. [89] proposed a semi-automated method for enhancing the ridge information using the estimated orientation image. The proposed method utilizes the skeleton image extracted using VeriFinger SDK to find a coarse orientation map. The coarse orientation field regularization is performed using the "zero-pole model" with a higher order polynomial function. Region of Interest (ROI) and singular points are manually annotated for latent fingerprints and the experiments are conducted using the NIST SD-27 database. The estimated orientation field monotonically increased the matching accuracy over all the quality bins of latent fingerprints. In 2011, Yoon et al. [88], proposed a more robust orientation field estimation technique for latent fingerprint enhancement. For every small non-overlapping patch of fingerprint, a set of coarse orientation fields are initially computed using the Short-Time Fourier Transform (STFT). A set of hypothesized orientation fields using randomized RANSAC based hypothesize-and-test paradigm are generated. Non-overlapping random orientation patches are chosen and tested for orientation consistency based on predefined thresholds. The best-fit regularized orientation field parameter is chosen to enhance the latent fingerprints. Experiments are performed using VeriFinger 4.2 SDK on latent fingerprints from NIST SD-27 against a combined gallery of NIST SD-27 and NIST 14 databases. The enhancement algorithm shows the rank-1 identification accuracy improvement from 12% to 26%. In 2012, Feng et al. [34], inspired from spelling correction methods employed in natural language processing, proposed an approach that makes use of the prior knowledge of ridge structure in fingerprint enhancement. A dictionary of reference orientation patches is created using ground truth orientation field and a compatibility constraint between neighboring orientation patches is also applied. Orientation field estimation for latent fingerprint is then posed as an energy minimization problem, solved using a loopy belief network. The average estimation error of orientation (in degrees) is used as the performance metric and is found to be at least $18.44°$ for the proposed network.

The term quality has different meanings in biometrics and forensic science communities. In 2013, Hicklin et al. [40] distinguished the concepts of clarity and quality, though the latent print examiners tend to use them synonymously. Clarity is defined as the ability to discern the presence or absence and attributes of features while quality depends on the number of features present. Hence, high clarity regions would be of low quality, if only very few features are available. A prototype of GUI based Latent Quality Assessment Software (LQAS) was created to manually annotate the local clarity regions. A color coding scheme with five levels of clarity was proposed as shown in Fig. 14. The color coded clarity map is visually informative for manual experts and ensures rapid analysis of local regions. The study on local clarity annotation and value determination concluded that there is a strong inter-examiner consistency in clarity boundary assessment but different examiners tend to vary while assigning a clarity value to different regions.

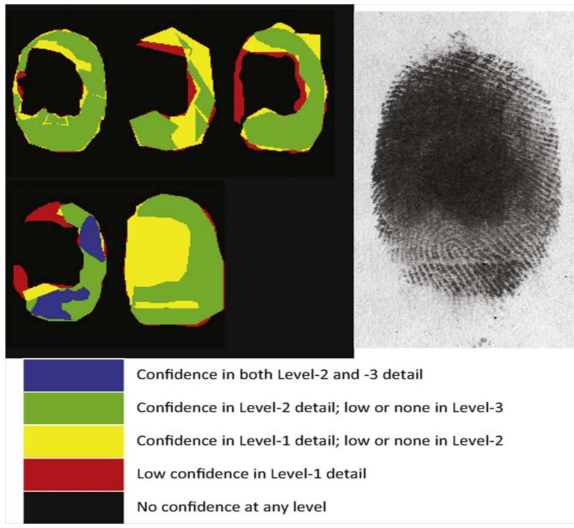


Fig. 14. A color coding based scheme with five different levels of clarity values. The clarity regions are manually annotated using the prototype of GUI based Latent Quality Assessment Software (LQAS). Image duplicated from [41].

Latent fingerprint quality assessment and enhancement is a challenging open-ended problem. Extracting orientation field from latent fingerprint requires manual input in terms of singular points and ROI. There is a huge scope of improvement by developing improved automated techniques for singular point detection as well as segmentation. Quality assessment can either refer to image capture quality or biometric quality which is a direct measure of the amount of useful information in a latent fingerprint image. In literature, the available information is measured in terms of the number of confident minutiae extracted. However, the information depends on many other factors such as the size of foreground information available, the region of the finger's surface that is deposited, and the clarity of fingerprint ridges. Extracting these features, though would be challenging, could provide an effective robust quality measure. Also, quality assessment can be made matcher independent or matcher dependent, as different matchers can produce different results for the same input image. Selection of the appropriate metric depends on the application as well as the algorithm used. Quality can be enhanced by not only improving the confidence of the features to be extracted but also by predicting the missing features in latent fingerprints. The latter technique increases the amount of information available for matching and can be given more focus in the future. Also the performance of the quality enhancement process is evaluated by the improvement in matching performance, which in turn depends on lots of other factors. Hence, thereupon some metrics has to be developed to evaluate the performance of quality enhancement as such.

D. Latent Fingerprint Feature Extraction

Features are the most succinct and precise representation of any data. Fingerprint, basically assumed to be unique, needs a very robust feature representation to maintain the uniqueness. In case of low information content and poor quality of ridge information, latent fingerprint feature extraction is a very challenging task. It is noteworthy to observe that for latent fingerprints shown in Fig 2, even manual annotation of features can be an arduous and erroneous process. Broadly, the fingerprint features can be classified into three categories - overall ridge flow pattern (Level 1), minutiae points (Level 2), and extended features (Level 3) such as dots, pores, and incipient ridges.

1) **Level 1:** The overall ridge flow pattern in a fingerprint is represented as Level 1 features. The ridges often flow smoothly, in parallel, except in a few points which are distinctively marked by high curvature or sudden termination of ridges. These points of ridge flow abnormality are called singular points. As shown in Fig. 15(a), there are two types of abnormalities in ridge flow pattern - cores and deltas. Henry [38] defined a core point as the "north most point in the inner most ridge line". Based on the occurrence and position of the core and delta points, fingerprints can be broadly classified into five categories: whorl, loop (left and right), arch, and tented arch. To determine the ridge pattern type and capture the singular points, fingerprint images should be captured at least at 300ppi resolution.
2) **Level 2:** The minutiae constitutes level 2 features. Minutiae are local features of a fingerprint and represent some discontinuity in the flow of ridges. The ridge flow consists of two types of discontinuities - ridge bifurcation and ridge ending, as shown in Fig. 15(a). Ridge bifurcations are points where a single ridge splits and continues as two different ridges whereas ridge endings are sudden spontaneous ridge terminations. Other general discontinues in ridge flow are lakes, islands, independent ridges, spurs, and crossovers. Every minutia is represented as $<x, y, \theta>$ where (x, y) refers to the 2-D spatial location of the minutia and θ refers to the orientation of the ridgeflow at (x, y). To extract minutiae, the fingerprint image must be captured at a resolution of at least 500ppi.
3) **Level 3:** Level 3 features [45] are fine and intricate features of fingerprint ridges. Features such as pores, dots, incipient ridges, ridge width, shape, edge contour, scars, breaks, and creases can be grouped into level 3 features, as shown in Fig. 15 (b). Although level 3 features are more distinctive in nature, not many automatic feature extraction algorithms exist owing to the challenging nature of the problem. To extract level 3 features, the fingerprint images should be captured at a very high resolution of more than 1000ppi.

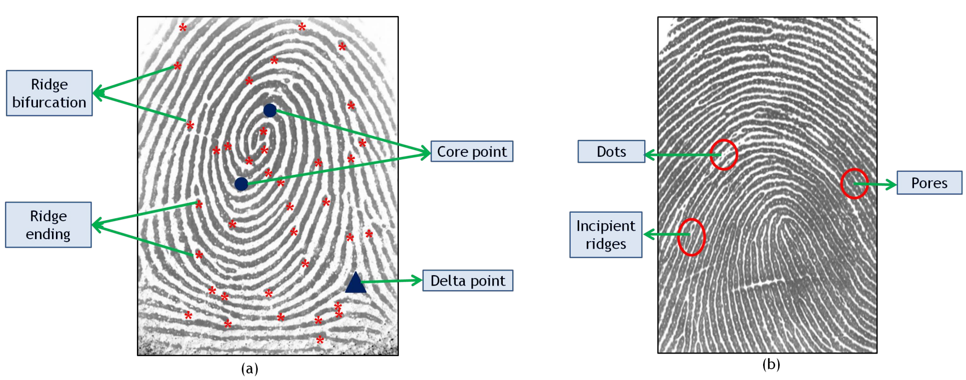
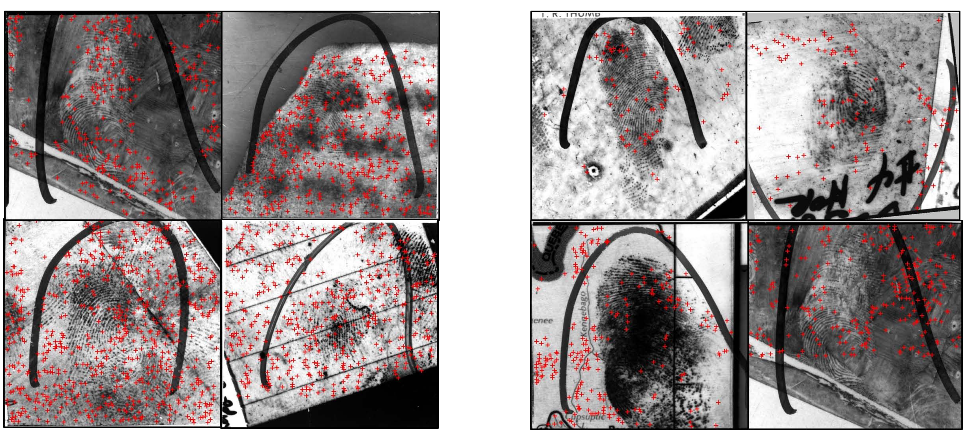


Fig. 15. Different types of features extracted from fingerprint. (a) shows Level-1 and Level-2 features and (b) shows Level-3 features.

In an attempt to perform fingerprint indexing using level-1 features, Feng and Jain [31] in 2008, proposed a background database filtering method. Filtering was performed in three cascaded stages using three different features - pattern type, singularity point similarity, and orientation field similarity. In their experimental study, 258 latent fingerprint images from NIST SD-27 were matched against a combined database of $10,258$ fingerprint images from NIST-4, NIST-14, and NIST SD-27 databases. The penetration rate of 39% was reported with an accuracy of 97.3%. It was also observed that the rank-1 identification accuracy increased from 70.9% to 73.3%. To automatically predict Level-1 features, Su and Srihari [76] in 2010, proposed core point detection of latent fingerprints using Gaussian process. The prior joint Gaussian distribution of singular points was learnt and regression was applied to predict the location of singular points. The results were compared with the standard Poincare Index (PI) method [48]. The Gaussian process models were trained using fingerprints from the NIST-4 database and tested on the NIST SD-27 database. Ground truth orientation field was obtained by simple gradient method and the ground truth core points were marked manually. The proposed method produced a core point prediction accuracy of 84.5% compared to the PI method having 69% accuracy.

Automatic extraction of level-2 features has been attempted on latent fingerprints with very little success. To better understand the performance of minutiae in actual scenarios, Puertas et al. [68], in 2010, compared manual minutiae extraction with automatic minutiae extraction using COTS. The matching performance of latent fingerprints with plain and rolled fingerprints was also compared. A database was created having latent, plain and rolled fingerprint of 50 subjects with an extended gallery of 2.5 million ten-print cards from the Department of Spanish Guardia Civil. The automated system marked, on an average, 31.2 minutiae in the latent prints while the experts marked an average of 25.2 minutiae. Four different experimental scenarios were adopted: (1) using manually annotated minutiae, (2) with automatically extracted minutiae, (3) using top 12 manually annotated minutiae based on confidence, and (4) using top 8 manually annotated minutiae, based on confidence. The performance accuracy of latent fingerprint matching decreased in the same order specified. The authors also mentioned that the quality assessment of latent fingerprints is an open problem that needs to be addressed. In 2010, Paulino et al. [66] attempted to fuse manually marked and automatically extracted minutiae for latent fingerprint matching. Latent fingerprints were enhanced by orientation field reconstruction using the extracted minutiae. The matching performance of these enhanced latent fingerprints was found comparable with the manually marked latent fingerprints. To further improve the performance of manual annotation, different levels of rank and match score fusion were performed. Experiments were performed using latent fingerprints in NIST SD-27 with a combined background database of NIST SD-27 and NIST-14 databases. It was observed that highest rank and boosted-max score fusion performs better than all other fusion methods. In 2011, Jain and Feng [43] provided a complete analysis of latent fingerprint matching with increased number of features and improved matching methods. The feature set extracted from fingerprints were singular points (core and delta), ridge flow map, ridge wavelength map, ridge quality map, fingerprint skeleton, minutiae points, ridge correspondence, and level-3 features (dots, incipient ridges and pores). Features were manually annotated in latent fingerprints. Both local and global matching methods were performed with and without using the additional level-3 features, to study the effect of these additional features. Extensive experiments were performed using 1000ppi latent fingerprints from NIST SD-27(A) with an extended background database of NIST SD-4, NIST SD-14, and NIST SD-27(A). The results show that the extended features were useful and may be utilized only when minutiae extraction is poor. Rank-1 identification accuracy increased from 34.9%, when only minutiae features were used, to 74% when all the features were used. In 2012, Paulino et al. [65] proposed a minutiae alignment technique for latent fingerprints using local descriptor based Hough transform. Minutiae were manually annotated for latent fingerprints while an automated fingerprint feature extractor was used to extract minutiae for background rolled fingerprints. Minutae Cylinder Code (MCC) [21] was used as the local descriptor for minutiae. Minutiae correspondences were established using a simple bounding box algorithm and euclidean distance measure. Experiments were conducted by matching latent fingerprints in the NIST SD-27 database against the combined gallery of NIST SD-27 and NIST-14 using a normalized similarity score metric. The normalized match scores showed a rank-1 identification accuracy of 57.4% when the proposed matcher was combined with the COTS matcher. In 2008, Vatsa et al., [82] proposed a method to combine pore and ridge features with minutiae for improved verification. Nine different indexing measures were proposed to combine level-1, level-2, and level-3 features. RDWT based local quality analysis is performed. The experiments were performed using 150 high resolution latent fingerprints having level-1, level-2, and level-3 features manually annotated. Quality based likelihood ratio provided a high rank 20 identification accuracy of 95.35%.



(a) (b)

Fig. 16. Sample latent fingerprints from NIST SD-27 showing spurious minutiae extracted by (a) NBIS and (b) VeriFinger 6.0 SDK

The ultimate aim of latent fingerprint research is to develop a “lights-out” system that can automatically extract valid features from a given latent fingerprint. Fig. 16 shows many spurious minutiae extracted using NBIS and VeriFinger 6.0 SDK. In general, it is observed and accepted that the standard algorithms and procedures practiced for live-scan fingerprint matching do not work on latent fingerprints effectively. The problem of latent fingerprint feature extraction can be viewed as a different problem, rather than an extension or a variation of ten-print fingerprint feature extraction. Though minutiae are the most commonly and widely accepted fingerprint features, in case of latent fingerprints, minutiae based representation may not be distinctive. Some reasons to think beyond minutiae are discussed below:

- Additional features in combination with minutiae can identify a fingerprint with increased robustness and confidence.
- Reliable extraction of minutiae from poor quality fingerprints is still a challenge.
- Certain non minutiae based approaches perform better when the area of the fingerprint captured is very small, leading to small amount of minutiae information.

Some additional properties that might be considered for latent fingerprint feature extraction are as follows:

- Detecting the size of the informative region available in a latent fingerprint can enable us to choose an appropriate technique for matching.
- Some regions of a fingerprint surface are more informative than the others. Automatic detection of the actual fingerprint region available in the lifted print may provide a better understanding of the actual amount of information available to us.
- The availability of singular points in ridge flow in the lifted fingerprint can provide us additional information. The ridge flow and minutiae extracted around singular points provide distinctive information and are more reliable.

E. Latent Fingerprint Matching

The aim of latent fingerprint matching process is to find a similarity or distance score between the two features of gallery and probe latent fingerprints. The matching process should attempt to increase the inter-class variations while decreasing the intra-class variations. Fig. 17 shows multiple latent fingerprints of the same finger exhibiting extreme intra-class variations. Latent fingerprint matching becomes a complex problem as it has to provide a valid match with just the available limited and noisy features.

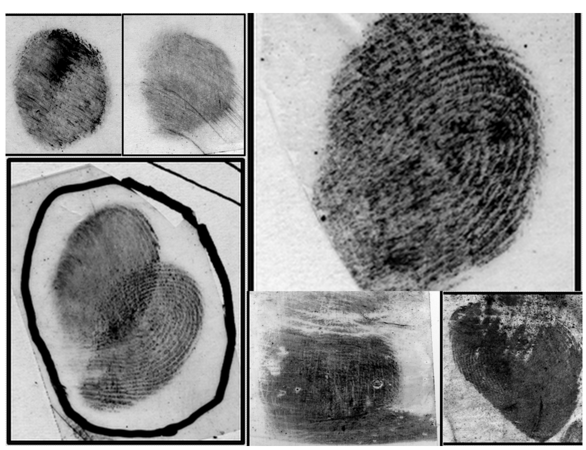


Fig. 17. Sample images showing high intra-class variation in latent fingerprints captured from the same finger. Images obtained from the ELFT-EFS public challenge dataset [4].

Jain et al. [44] proposed a preliminary automatic latent fingerprint matching algorithm in 2008. Features such as minutia, ridge flow, quality map, and orientation field were manually annotated for latent fingerprint matching. The singular points were detected automatically for latent fingerprints and were shown to work better than the Poincare Index (PI) method for latent fingerprints. Two different feature matching strategies were performed: (i) Local minutiae matching and (ii) Global minutiae matching. In local minutiae matching, two different descriptors were used to represent the local minutiae: orientation based descriptor and neighborhood minutiae based descriptor. In global minutia matching, a greedy approach was followed, where only the top five matches of the entire minutiae set were considered. Weighted sum score fusion of orientation based and neighborhood minutiae based matching was performed. The experiments were performed using latent fingerprints from NIST SD-27 against a combined gallery of rolled fingerprints from NIST SD-27 and NIST 4. An increased rank-1 accuracy of 79.5% and a rank-20 accuracy of 93.4% were obtained for the proposed matching method. Feng et al. [33], in 2009, proposed a method to match latent fingerprints against the corresponding fusion of flat and rolled fingerprints. The features used were minutiae, quality map, and orientation estimation. Three levels of fusion were separately performed - rank level, match score level, and feature level. Rank level fusion was performed using the highest rank method and Borda count method. Match score level fusion was performed using min, max, sum, product and boosted-max score fusion methods. In the boosted-max match score fusion method, the scores corresponding to genuine matches were boosted by a factor because the spatial transformation in genuine matches was consistent. For feature level fusion between flat and rolled fingerprints, the features were considered from rolled fingerprints in overlapping regions while in non-overlapping regions, features from corresponding image were considered. The experiments performed using the ELFT-EFS database showed that boosted-max provided the maximum rank-1 identification accuracy of 83% compared to 57.8% for flat and 70.4% for rolled fingerprints. Dvornychenko [30] performed fusion for latent fingerprint matching in three different strategies: (i) fusion of the output of two different classifiers with same feature set, (ii) fusion of the output of same classifier with two different feature sets, and (iii) fusion of the output of two different classifiers with two different feature sets by a specific combination strategy. Experimental results showed that a rank-1 performance boost of $6-15\%$ is obtained when multiple features were given to the same classifier and fused. Recently in 2012, Mikaelyan and Bigun [57], established the ground truth of minutiae level correspondences for the publicly available latent fingerprint database NIST SD-27. The authors performed verification tests using two different publicly available matchers, Bozorth3 [12] and k-plet [22], yielding an EER (Equal Error Rate) of 36% and 40% respectively. The results suggest that both the matchers have poor ability to separate genuine and imposter matches in latent versus ten-print matching experiment. However, in an identification setup, at higher ranks, k-plet provided better accuracy than bozorth3 matcher. Kargel et al. [46] in 2012, performed a comparative study of existing exemplar fingerprint matching systems for latent fingerprints. Evaluation was performed to understand the usability of the existing exemplar matching systems and exemplar quality metrics for latent fingerprints. A multi-variate latent fingerprint database, having 480 latent impressions was created. The experiments were performed on four open source fingerprint matching systems: Source-AFIS [83], FVS [63], NBIS [12]. Biometrics SDK [1], and COTS: Innovatrics IDKit PC SDK [10]. The overall analysis showed that none of the existing exemplar systems used in this experiment could be used as a valid and confident matching system for latent fingerprint matching. It was also observed that the standard quality assessment metric

NFIQ in NBIS, was not an efficient quality measure for latent fingerprints. In 2013, Liu et al [54] proposed an automated feedback mechanism to refine the set of features that are similar between the rolled and latent fingerprints. Using this feedback mechanism the rank list is re-ordered to achieve improved performance. The experiments performed using latent fingerprints from the NIST SD-27 and WVU databases with an extended gallery using NIST SD-14 show an average improvement of about 10%.

Most of the feature extraction and matching techniques in literature have been proposed for matching level-2 (minutiae) and level-3 features from flat and rolled fingerprints. The primary challenge for matching latent fingerprints is the extraction of valid reliable features. Reliable and accurate matching techniques could be devised along with the development of feature extraction techniques. The growth in feature extraction methods would guide the growth in feature matching techniques, as well. Another challenge in latent fingerprint matching, would be to transform the human cognition into automated systems to match fingerprint features [73].

F. Summary

The problem of latent fingerprint matching is naturally challenging due to the limited information availability and noisy information. An automated latent fingerprint matching system would be a significant contribution towards crime scene analysis and other forensic applications. To develop such a "lights-out" system, the individual modules, explained in this section, must be addressed thoroughly. A comparative study of the most recent research works in individual modules has been performed in Table II. From the table it can be seen that the research in every single module is at its preliminary stage allowing a large scope of research in this field. With manual annotation of minutiae features, a maximum accuracy of about 75% can be achieved in the NIST SD-27 database. Growth should occur in parallel and in all the modules of a latent fingerprint matching system to overcome the challenges of latent fingerprint matching. The development of automated systems for latent fingerprint matching requires forensic domain experts. A lack of systematic methodology and defined procedure for manual matching of latent fingerprints impediments the growth of automated systems. The knowledge of on-field forensic experts and computational biometric researchers should be brought together to better understand practical challenges in the development of automated systems for latent fingerprint matching.

IV. Importance of Evidential Value of Latent Fingerprints

The preliminary assessment by a manual examiner or any automated latent fingerprint matching system is to analyze whether the given latent fingerprint has minimum information required to make a match and act as evidence. The metric used to quantify this assessment is called the evidential value of a latent fingerprint. In 1892, Galton [35] defined the measure of evidential value as the probability that two fingerprints under consideration belong to two different persons. The studies performed, thus far, for evidential value estimation can be classified into two types - feature modeling techniques, where statistical modeling of features is performed for evidential value estimation and match score modeling technique, where match scores are analyzed for evidential value estimation. In 2011, Choi

Process	State of art	Technique used	Accuracy
Segmentation	Choi et al. [23]	Frequency and orientation tensors	Rank-1 identification accuracy of 16.28%, 35.19% in NIST SD-27 and WVU DB
	Zhang et al., [91]	Adaptive Total Variational Model	No evaluation is performed.
Quality Assessment	Yoon et al. [90]	Ridge Clarity Maps	Improves Rank-100 identification accuracy from 69% to 86% in NIST SD-27 and WVU DB
Enhancement	Yoon et al. [88]	STFT + RANSAC	Improves Rank-20 identification accuracy of from 10% to 51% in NIST SD-27
	Feng et al. [34]	Dictionary of orientation patches	Rank-20 identification accuracy of 35% in NIST SD-27
Automatic Feature Extraction	Paulino et al. [64]	Hough transform	Rank-1 identification accuracy of 57.4% in NIST SD-27 and WVU DB
Feature Matching	Jain and Feng [43]	Local and global matching	Rank-1 identification accuracy of 74% on NIST SD-27(A) database.

TABLE II
STATE OF ART TECHNIQUES PROPOSED FOR THE INDIVIDUAL STAGES IN AUTOMATIC LATENT FINGERPRINT MATCHING.

et al. [24] proposed a match score modeling technique for evidential value estimation for fingerprints using a measure called the Non-Match Probability (NMP). For a given similarity score s, NMP value is calculated as

$$NMP = P(I|s) = 1 - P(G|s) \tag{1}$$

where $P(I|s)$ and $P(G|s)$ are the probability that the given match score corresponds to an imposter match or a genuine match respectively. Following the theory of total probability, NMP is computed as follows,

$$NMP = P(I|s) = \frac{P(s|I)P(I)}{P(s|I)P(I) + P(s|G)P(G)} \tag{2}$$

where the priors $P(I)$ and $P(G)$ denote the additional evidence that might be available. Also, NMP has a direct relation with the Probability of Random Correspondence (PRC) [62] and the Likelihood Ratio (LR) [60] as given by the following two equations.

$$NMP = P(I|s) = \frac{PRC \times P(I)}{P(s)} \tag{3}$$

$$NMP = P(I|s) = \frac{1}{1 + LR\frac{P(G)}{P(I)}} \tag{4}$$

Estimating NMP values is much more critical in latent fingerprints as it provides the confidence of match or non-match in a forensic evidence comparison. In 2012, Nagar et al. [59] performed a thorough analysis of evidential value estimation for latent fingerprints. An extended NMP calculation was proposed that calculates NMP values as a conditional probability distribution using some prior information about latent fingerprints. Different functions such as the number of minutiae, quality, and latent print area were used as priors to calculate the NMP. Analysis was done to observe the variation of NMP with respect to changes in the prior functions, individually. Due to the paucity of latent fingerprint database, simulated database of latent fingerprints was created by cropping random partial regions from two full fingerprint databases - NIST SD-14 and Michigan State Police. Extensive experiments were performed on four latent fingerprint databases using two Commercial Off the Shelf (COTS) matchers, to study the evidential value of a latent fingerprint match. The significance of evidence associated with an NMP match was calculated using a measure called conclusiveness. The conclusiveness of a latent-full print matching allowed latent fingerprints to be confidently used as evidence in the court of law. The authors also proposed a framework for forensic experts to be able to use this empirical approach for calculating the evidential value of a latent fingerprint match in practical scenarios.

In 2013, Ulery et al [81] experimentally analyzed the value of latent fingerprint with respect to the features and clarity of latent fingerprints. The main motive of their research was to study the correlation between the number of minutiae and other features with the value determination capability of a human expert. For a threshold of 12 or more minutiae, it was observed that 84% of the experts were correctly able to associate VID value to the latent print. However, it was concluded that only the count of minutiae, and not clarity and other features that majorly affects value determination. These correlations were verified through experimental observations; however, a strong theoretical basis would serve better in evidential value assessment. The importance of mathematically modeling the evidential value is to inculcate it in the process flow of automated latent fingerprint matching. When a group of latent fingerprints is lifted by forensic experts from a crime scene, the automated system should first find the candidate list of fingerprints eligible for matching process. The remaining fingerprints should be discarded as they may not have enough information to make a confident match. This procedure would reduce the number of latent fingerprints required to match thus reducing the cumulative processing time of the system.

V. Baseline Experiments for Latent Fingerprints

To further understand and quantify the capabilities of a latent fingerprint matching system, we have performed certain baseline experiments on two of the publicly available databases. This section presents various latent fingerprint databases available for research and some of the baseline results performed on these databases.

A. Latent Fingerprint Database

One of the major limiting factors in conducting research in latent fingerprints is the lack of large publicly available databases acquired under real environments. There are several challenges in collecting a fingerprint database:

- Collecting and lifting latent fingerprints require professional expertise and is difficult to collect for amateurs. Further, lifting and collecting latent fingerprints is a time taking process.

Database	# Classes	# Images	Characteristics
NIST SD-27A [18]	258	258	Latent to rolled fingerprint matching Manually annotated features available 500ppi and 1000ppi exemplars
IIIT-D Latent Fingerprint [69]	150	1046	Latent fingerprint with mated 500ppi and 1000ppi exemplars Slap images of 500ppi images are provided Latent images are lifted using black powder dusting process and captured directly using a camera
IIIT-D SLF [70]	300	1080	Simultaneous latent fingerprint with mated slap 500ppi exemplars 2 sessions of simultaneous latent fingerprint was lifted using black powder dusting Latent fingerprint images have to be cropped from simultaneous latent fingerprints
WVU Latent Fingerprint [65]	449	449	Latent to rolled fingerprint matching Database not publicly available Manually annotated features available 500ppi and 1000ppi exemplars
ELFT-EFS Public Challenge #2 [4]	1100	1100	500ppi and 1000ppi images in WSQ compressed format Database not publicly available Manually annotated features available

TABLE III
CHARACTERISTICS OF LATENT FINGERPRINT DATABASES.

- Only few of the available latent fingerprint lifting techniques are cheap and easily procurable. The remaining techniques can be handled only by certified experts.
- Simulating real time environments is very tough as latent fingerprints collected from crime scenes have huge variation in terms of quality and possible backgrounds.
- It is challenging to capture databases with enough variability (such as multiple sensors, multiple backgrounds, multiple sessions, and varying quality).

There are three publicly available latent fingerprint databases namely: NIST SD-27 [18] database, IIIT-D latent fingerprint database [69], and IIIT-D SLF database [70]. These databases are captured at different times, in different environments, and have significantly different characteristics. Table III provides the details of all three databases and two other latent fingerprint databases used in literature.

B. Experimental Protocol and Analysis

The baseline accuracies on two commonly available public latent fingerprint databases - NIST SD-27 [18] and IIIT-D latent fingerprint database [69] are computed using two exemplar based fingerprint matching systems: NBIS by NIST [12] and VeriFinger by Neurotechnology [15]. For both the databases, the latent fingerprints act as probe while the rolled or flat fingerprints are the background gallery. The features of latent fingerprints are marked manually whereas the feature extraction for rolled fingerprints and matching is done automatically using the two systems. The results are reported in terms of the identification performance. Table IV shows the rank-10 identification accuracy and Cumulative Match Characteristic (CMC) curves are shown in Figs. 18 and 19. Some key analyses obtained from the results are as follows:

	NIST SD-27	IIIT-D Latent
Manual Annotation	18.23	-
NBIS	9.3	14.78
VeriFinger	24.81	18.68

TABLE IV
RANK-10 IDENTIFICATION ACCURACY (%) ON THE NIST SD-27 AND IIIT-D LATENT FINGERPRINT DATABASES USING MANUALLY ANNOTATED FEATURES, NBIS, AND VERIFINGER. IT IS TO BE NOTED THAT THE IIIT-D LATENT FINGERPRINT DATABASE DOES NOT HAVE MANUALLY ANNOTATED FEATURES.

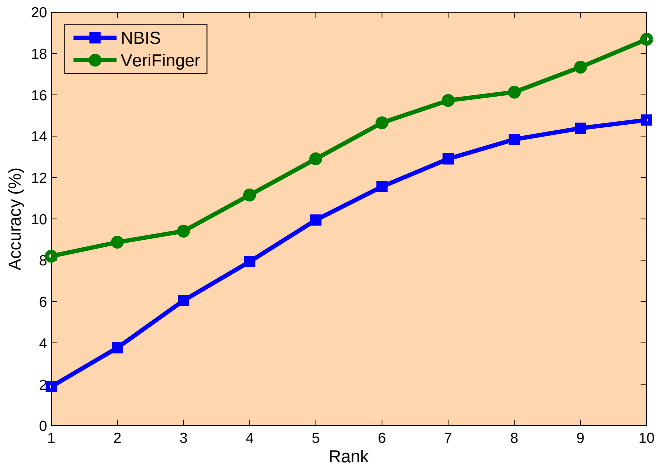


Fig. 18. Rank-10 identification accuracy (%) on the IIIT-D latent fingerprint database using NBIS and VeriFinger.

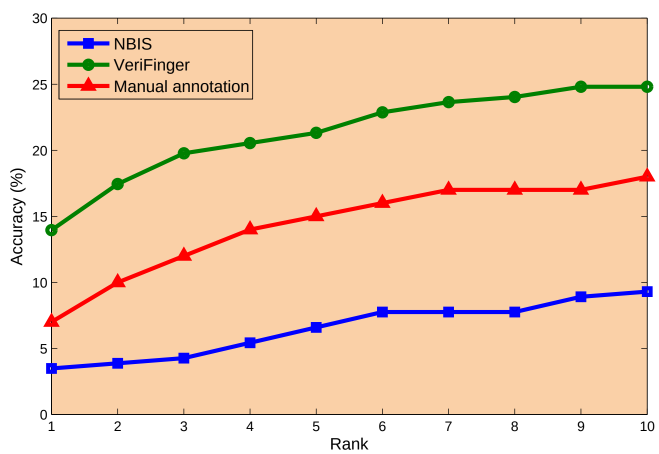


Fig. 19. Rank-10 identification accuracy (%) on the NIST SD-27 latent fingerprint database using NBIS, VeriFinger, and manually annotated features.

- One of the primary purpose of conducting the experiments is to understand the success of existing ten-print matching systems for latent fingerprint. The results in Table IV demonstrate that the existing ten-print matching systems perform poorly for latent fingerprint matching. This also implies the difficult nature of the problem of latent fingerprint matching.
- To evaluate the performance of feature extraction, the number of minutiae extracted by the two matchers are compared. In the NIST 27-SD database, manual annotation had an average of 21 minutiae whereas VeriFinger extracted an average of 116 minutiae and NBIS extracted an average of 339 minutiae. In the IIIT-D database, VeriFinger extracted an average of 43 minutiae and NBIS (mindtct) extracted an average of 46 minutiae. From Fig. 20, it can be visually observed that NBIS extracts a lot of spurious minutiae in latent fingerprints. Further, the numbers also suggest that existing matching systems are not reliable for extracting features from latent fingerprints.
- Figs 21, and 22 show the genuine and imposter match score distributions on the IIIT-D latent fingerprint database by NBIS and VeriFinger matchers respectively and Figs 23, and 24 show the score distributions of the two matchers on the NIST SD-27 database. From the plots, it can be observed that the distribution overlaps in almost all the cases. Scores generated from the matchers, NBIS and VeriFinger, are not efficient enough for separating the genuine and imposter matches on these databases.

(a)

(b)

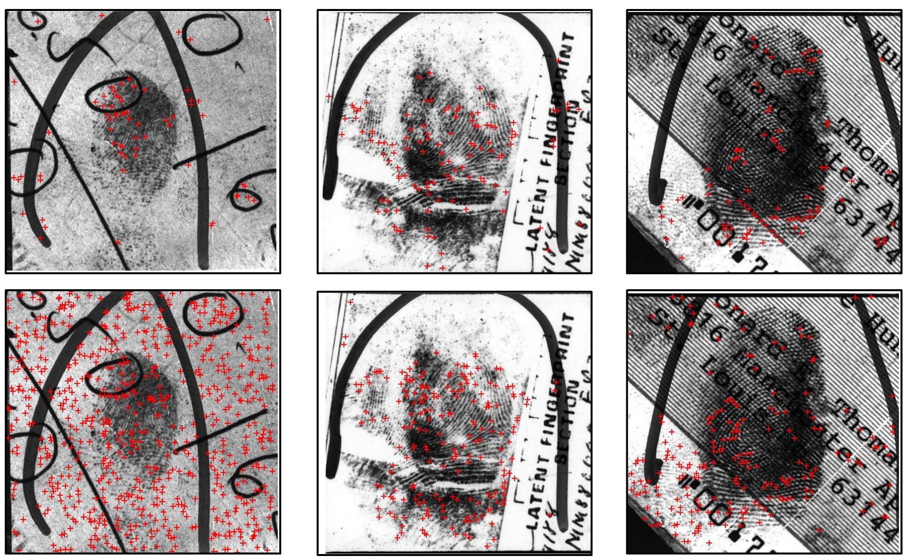


Fig. 20. Sample latent fingerprints from NIST SD-27 shows the minutiae extracted by (a) VeriFinger 6.0 SDK and (b) NBIS. It can be observed that NBIS extracts a lot of spurious minutiae compared to VeriFinger.

VI. Conclusion

Research in overall automated latent fingerprint matching technology is still in its preliminary stages and not rigorously taken up. The basic challenge can be rooted back to the lack of large public latent fingerprint database available for research. There is no publicly available database that contains mated latent fingerprints lifted from multiple surfaces using multiple lifting methods. A combined database having the latent fingerprints of the same finger lifted from various surfaces such as a door knob, a plastic handle, a wooden plank, and a bank rupee note can open new research

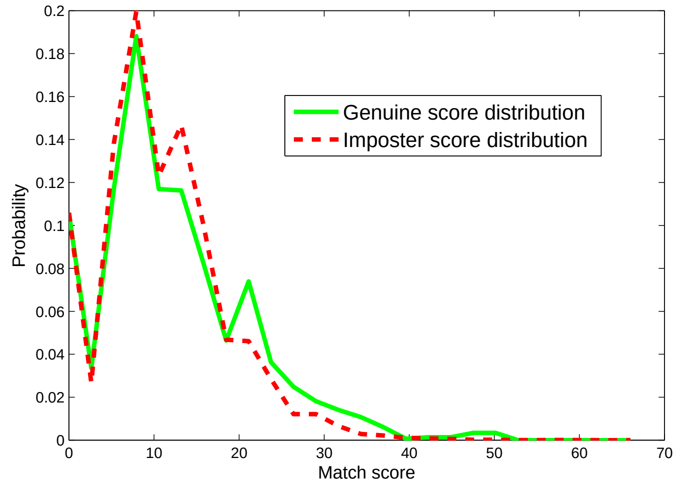


Fig. 21. Genuine and imposter match score distributions obtained using NBIS matcher on the IIIT-D latent fingerprint database.

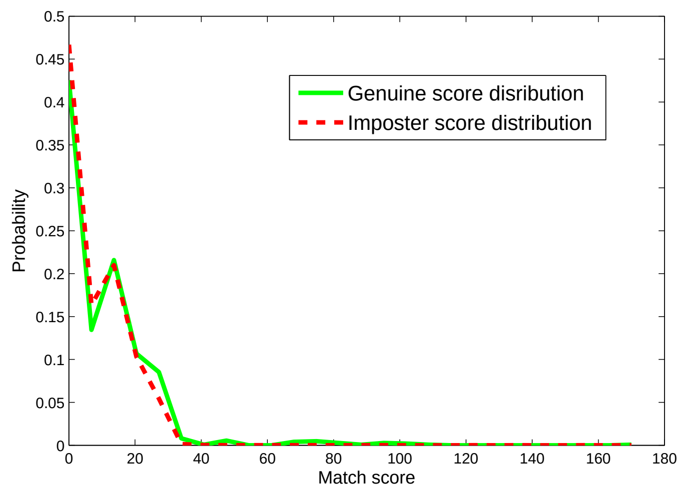


Fig. 22. Genuine and imposter match score distributions obtained using VeriFinger matcher on the IIIT-D latent fingerprint database.

problems and encourage extensive research in latent fingerprint matching. Table V summarizes the list of features and evaluation metrics that have been used for individual modules in latent fingerprint matching. It can be observed that most of the features have been extended from full fingerprint analysis literature. As the problem of latent fingerprints has different properties and challenges than full fingerprints, identifying latent fingerprint specific features can be a good direction to work in the future. Also, the metric primarily used to evaluate both the intermediate processes and complete matching algorithm is rank-k identification accuracy. Although improving the matching performance is the eventual aim of an automated matching system, defining some evaluation metrics to examine the different stages as such may help to devise better techniques in the future.

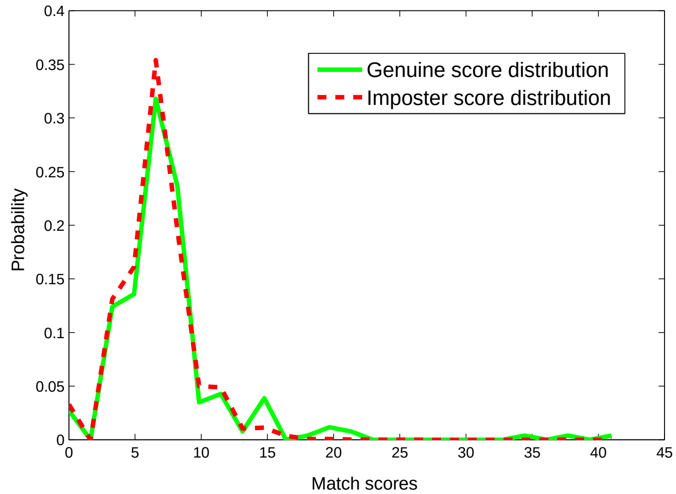


Fig. 23. Genuine and imposter match score distributions obtained using NBIS matcher on the NIST SD-27 latent fingerprint database.

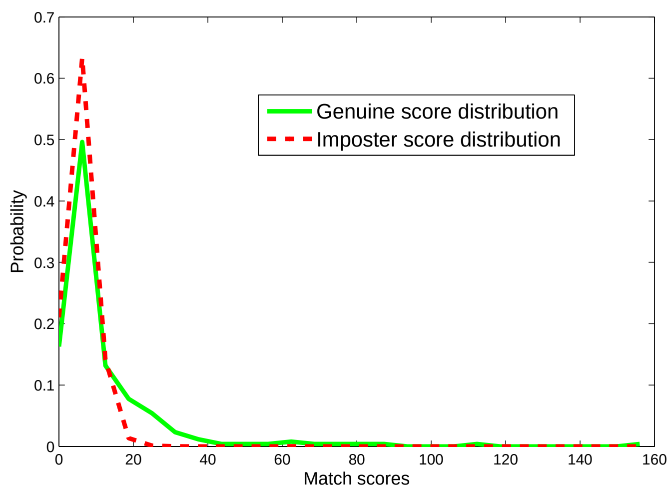


Fig. 24. Genuine and imposter match score distributions obtained using VeriFinger matcher on the NIST SD-27 latent fingerprint database.

APPENDIX A
FINGERPRINT FORMATION

The fetal development of fingerprints (epidermal ridges) is very important in understanding about the structure, growth, information and uniqueness of fingerprints. The formation of fingerprints is a mechanical process, resulted by a constant compressive force applied on a plain epidermal skin for a prolonged period. Fingerprints can be compared to wrinkles that appear on skin when compressed, except for the fact that fingerprints do not wither off over time.

In 1892, Sir Francis Galton [35] demonstrated that epidermal ridge patterns do not change after the post-natal growth period. From then, several dermatoglyphic studies have been performed by forensic experts, genetic engineers, and anthropologists on the skin ridge patterns. The initial embryogenic studies on fingerprint can be traced back to Bonnevie [20] and Cummins [28] in 1927. Over the last century, embryonic development of human hands have been studied using several different

Process	Features used in literature	Evaluation metrics
Segmentation	1. Orientation tensor, frequency tensor [23] 2. Correlation strength [74] 3. Adaptive total variation (TV-LI) [91] 4. Directional total variation (TV-L2) [92]	1. Missed Detection Rate 2. False Detection Rate 3. Rank-K matching
Quality Assessment	1. NFIQ1.0 features, frequency domain analysis, local clarity analysis, orientation flow, radial power spectrum, ridge valley uniformity, Gabor filters, and minutiae count [41] 2. Gabor filters [61] 3. Ridge clarity map, number of minutiae [90]	1. VID and non-VID classification 2. Rank-K matching of different quality bins
Quality Enhancement	1. Dictionary of orientation patches [34] 2. Candidate orientation map, singular points [88], [89]	1. Average estimation error of orientation (in degrees) 2. Rank-K matching of different quality bins
Matching	1. Singular points, ridge flow map, ridge wavelength map, ridge quality map, fingerprint skeleton, minutiae points, ridge correspondence, level-3 features [43] 2. Orientation field, ridge flow, quality map, manual minutiae [44] 3. MCC descriptor for minutiae [65] 4. Manually and automated extracted minutiae [66], [68]	1. Rank-K matching

TABLE V
THE DIFFERENT PROCESS IN LATENT FINGERPRINT ANALYSIS, THE FEATURES USED IN LITERATURE FOR THE CORRESPONDING PROCESS AND ITS EVALUATION METRIC. MAJORITY OF THE FEATURES ARE EXTENDED FROM FULL FINGERPRINT ANALYSIS LITERATURE. ALSO, THE METRIC USED TO EVALUATE THE PERFORMANCE OF ANY INTERMEDIATE STAGE IS STILL RANK-K MATCHING PERFORMANCE.

methods [72], as follows

- using classical microscopy
- methods of electron microscopy
- methods of nerve structures
- methods of mathematical analysis

The fingerprint formation starts during the 6th week of embryonic development marked by the formation of volar pad [9], as shown in Fig. 25. For the next two weeks, there is a differential growth in the volar pads varying the position and size of pads for every finger of the palm. This differential growth eventually determines the size and shape of the fingers, distance between fingers, and the growth of epidermal ridges. As this growth phase is completely random, the outcome of the finger structure as well as the ridge patterns are random. This randomness makes the fingerprint patterns unique.

Around the end of 11th week, the volar pads regression results in the initial formation of the epidermal ridges, as shown in Fig. 26. The volar pads start compressing from all the directions

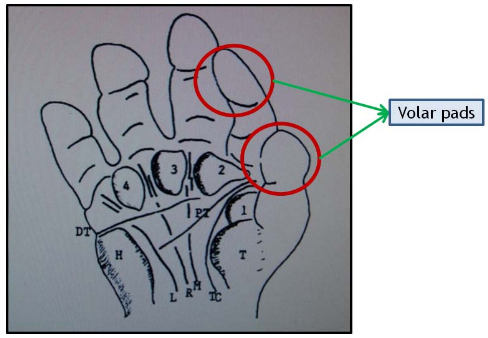


Fig. 25. Volar pad formation in human hand digits [19].

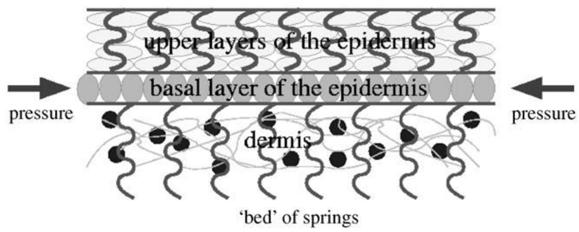


Fig. 26. Cross section of human skin showing the arrangement of epidermis, dermis and basal layer [50].

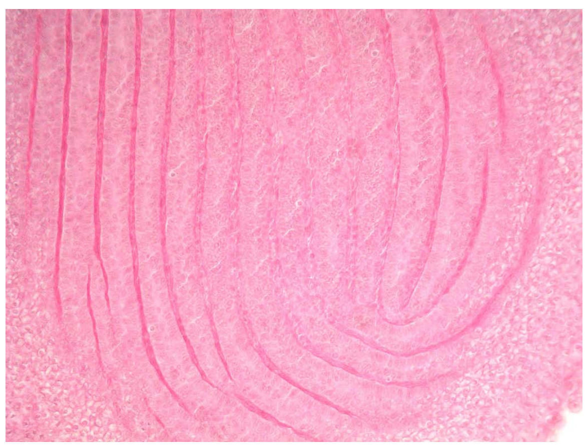


Fig. 27. Tangential section through the ventral surface of finger pad of 15-week-old fetus. Dark stained lines are the epidermal glandular folds arranged as the dermatoglyphic pattern called loop [72].

which can be seen as cell proliferations in basal(epidermis) layer. The cell proliferations project as small ridge patterns which rapidly grows from multiple pressure regions producing islands and branchings, called minutiae. These primary ridges increase in width and depth, over the next 2-3 weeks leaving a permanent mark in the basal layer. This process of formation of epidermal ridges can be imagined as the ripples formed in a thin layer of water, or a slight disturbance in the transverse motion of the air trough. The epidermal ridges can be seen in the tangential section of a fingerprint, as shown in Fig. 27.

Kucken and Newell [50] in 2004, attempted to mathematically model the formation of fingerprint by considering the skin (basal layer of the skin) as a thin plate. When a normal force is applied on a thin plate, buckling instability occurs, creating ripples in the direction perpendicular to the action of force. Buckling instability results in a plastic deformation of the surface due to the increased load

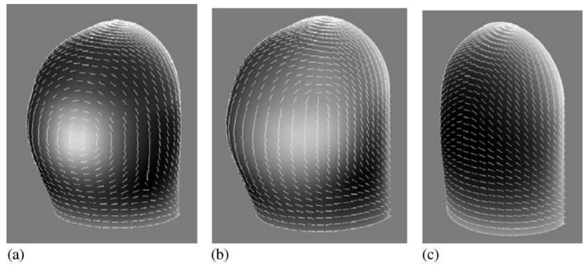


Fig. 28. Stress field spread over the entire finger during the differential growth of finger from 7th-10th week [49].

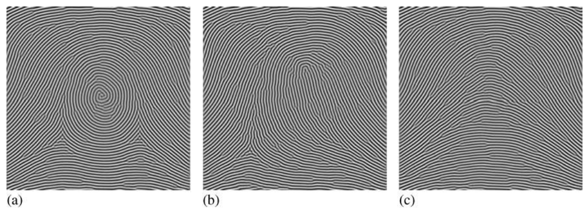


Fig. 29. Simulation of the ridge patterns for various types of fingers as mathematically modelled by Kucken and Newell [50].

more than the surface can hold. A stress field is formed over the entire finger surface, as shown in Fig. 28. The buckling instability in a thin plate is governed by the famous Von-Karman equations [67]. These equations provide a mathematical form for every single ridge that is formed. It can be thus explained that the canonical solution between two such equations is the minutiae (the point where two ridges meet). The buckling instability is mathematically formulated and by solving the Von-Karman equations, the position of minutiae are localized. The authors simulated the entire instability model and the resulting fingerprint patterns are shown in Fig. 29.

However all the factors that affect the formation of ridge configuration is not clearly defined. Some hypothesis that have been developed over the years and reviewed by Kucken [49] are:

- The folding hypothesis
- The nerve hypothesis
- The fibroblast hypothesis

Thus, a plenty of natural phenomenon contribute towards the forming of ridge patterns on the skin surface. Researchers in the past have tried to learn and understand this formation using plenty of approaches and gained insights into this highly random pattern. This knowledge obtained allows us to device better and more intelligent algorithms for fingerprint matching.

REFERENCES

[1] Biometric SDK, 2012. *http://sourceforge.net/projects/biometricsdk*.

[2] Biometrics Research Group Inc. *http://www.biometricupdate.com*.

[3] Case report - Shirley Mckie fingerprint scandal. *http://www.shirleymckie.com/reports.htm*.

[4] Evaluation of Latent Fingerprint Technologies (ELFT). *http://www.nist.gov/itl/iad/ig/latent.cfm*.

[5] Fact sheet - Integrated Automated Fingerprint Identification System (IAFIS). *http://www.fbi.gov/about-us/cjis/fingerprints_biometrics/iafis/iafis_facts*.

[6] FBI IAFIS - CJIS Division, 2010 Latent Hit of the Year. *http://www.fbi.gov/news/stories/2010/october/latent_102510/latent_102510*.

[7] FBI IAFIS - CJIS Division, 2012 Latent Hit of the Year. *http://www.fbi.gov/about-us/cjis/cjis-link/july-2012/2012-latent-hit-of-the-year*.

[8] FBI IAFIS - CJIS Division, Latent Hit of the Year Award Videos. *http://www.fbi.gov/about-us/cjis/fingerprints_biometrics/iafis/iafis_latent_hit_of_the_year*.

[9] Fingerprint formation. *http://ridgesandfurrows.homestead.com/FSG2.html*.

[10] INNOVATRICS s.r.o. IDKit PC SDK,. *http://www.innovatrics.com/products/fingerprint-identification-sdk, organization =*.

[11] Latent fingerprint processing techniques-selection & sequencing guide. *Chesapeake Bay Division, http://www.cbdiai.org/Reagents/main.html*.

[12] NBIS (NIST Biometric Image Software). *Developed by National Institute of Standards and Technology (NIST), http://www.nist.gov/itl/iad/ig/nbis.cfm*.

[13] A Review of the FBI's Handling of the Brandon Mayfield Case. *Unclassified executive summary, http://www.justice.gov/oig/special/s0601/exec.pdf*.

[14] The Innocence Project. *http://www.innocenceproject.org/*.

[15] VeriFinger by NeuroTechnology. *www.neurotechnology.com/verifinger.html*.

[16] CDEFFS: The Committee to Define an Extended Fingerprint Feature Set. *http://fingerprint.nist.gov/standard/cdeffs/index.html*, 2008.

[17] SWGFAST, Standard for simultaneous impression examination, ver. 1.0. *www.swgfast.org*, pages 1–20, 2009.

[18] Fingerprint minutiae from latent and matching tenprint images. *NIST Special Database 27*, 2010.

[19] D. Ashbaugh. Quantitative-Qualitative friction ridge analysis: An introduction to basic and advanced ridgeology. *CRC Press, FL*, pages 134–135, 1999.

[20] K. Bonnevie. Studies on papillary patterns of human fingers. *Journal of Genetics*, 15:1–111, 1924.

[21] R. Cappelli, M. Ferrara, and D. Maltoni. Minutia Cylinder-Code: A new representation and matching technique for fingerprint recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(12):2128 –2141, 2010.

[22] S. Chikkerur, E. N. Cartwright, and V. Govindaraju. K-plet and CBFS: A graph based fingerprint representation and matching algorithm. In *International Conference on Biometrics (ICB)*, 2006.

[23] H.-S. Choi, M. Boaventura, I. A. G. Boaventura, and A. K. Jain. Automatic segmentation of latent fingerprints. In *IEEE International Conference on Biometrics: Theory Applications and Systems (BTAS)*, 2012.

[24] H.-S. Choi, A. Nagar, and A. K. Jain. On the evidential value of fingerprints. In *International Joint Conference on Biometrics (IJCB)*, 2011.

[25] S. Cole. What counts for identity? The historical origins of the methodology of latent fingerprint identification. *Science in Context*, 12(1):139–172, 1999.

[26] S. A. Cole. More than zero: Accounting for error in latent fingerprint identification. *Journal of Criminal Law & Criminology*, 95:985, 2004.

[27] S. Crihalmeanu, A. Ross, S. Schuckers, and L. Hornak. A protocol for multibiometric data acquisition, a protocol for multibiometric data acquisition, storage and dissemination. *WVU Technical report*, 2007.

[28] H. Cummins and C. Midlo. Palmar and plantar epidermal ridge configuration (dermatoglyphics) in European-Americans. *American Journal of Physical Anthropology*, 9:471–502, 1926.

[29] I. Dror, C. Champod, G. Langenburg, D. Charlton, H. Hunt, and R. Rosenthal. Cognitive issues in fingerprint analysis: Inter-and intra-expert consistency and the effect of a target comparison. *Forensic Science International*, 208(1):10–17, 2011.

[30] V. Dvornychenko. Evaluation of fusion methods for latent fingerprint matchers. In *International Conference on Biometrics (ICB)*, 2012.

[31] J. Feng and A. K. Jain. Filtering large fingerprint database for latent matching. In *International Conference on Pattern Recognition (ICPR)*, pages 1–4, 2008.

[32] J. Feng, Y. Shi, and J. Zhou. Robust and efficient algorithms for separating latent overlapped fingerprints. *IEEE Transactions on Information Forensics and Security,*, 7(5):1498–1510, 2012.

[33] J. Feng, S. Yoon, and A. Jain. Latent fingerprint matching: Fusion of rolled and plain fingerprints. *Advances in Biometrics*, pages 695–704, 2009.

[34] J. Feng, J. Zhou, and A. Jain. Orientation field estimation for latent fingerprint enhancement. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(4):925–940, 2013.

[35] F. Galton. Finger prints. *Macmillan, London*, 1892.

[36] S. Gruhn and C. Vielhauer. Surface classification and detection of latent fingerprints: Novel approach based on surface texture parameters. In *International Symposium on Image and Signal Processing and Analysis (ISPA)*, pages 678–683, 2011.

[37] L. Haber and R. Haber. Error rates for human latent fingerprint examiners. In *Automatic Fingerprint Recognition Systems*, pages 339–360. Springer New York, 2004.

[38] E. R. Henry. Classification and uses of fingerprints. *Routledge & Sons, London*, pages 54–58, 1900.

[39] A. Hicklin. Latent quality survey. *Noblis Inc.*, 2007.

[40] R. A. Hicklin, J. Buscaglia, and M. A. Roberts. Assessing the clarity of friction ridge impressions. *Forensic Science International*,

226(13):106 – 117, 2013.

[41] R. A. Hicklin, J. Buscaglia, M. A. Roberts, S. B. Meagher, W. Fellner, M. J. Burge, M. Monaco, D. Vera, L. R. Pantzer, C. C. Yeung, and T. N. Unnikumaran. Latent fingerprint quality: A survey of examiners. *Journal of Forensic Identification*, 61(4):385–418, 2011.

[42] M. Hildebrandt, J. Dittmann, M. Pocs, M. Ulrich, R. Merkel, and T. Fries. Privacy preserving challenges: new design aspects for latent fingerprint detection systems with contact-less sensors for future preventive applications in airport luggage handling. *Biometrics and ID Management*, pages 286–298, 2011.

[43] A. Jain and J. Feng. Latent fingerprint matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(1):88–100, 2011.

[44] A. Jain, J. Feng, A. Nagar, and K. Nandakumar. On matching latent fingerprints. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, pages 1–8, 2008.

[45] A. K. 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*, 29(1):15–27, 2007.

[46] R. Kärgel, M. Hildebrandt, and J. Dittmann. An evaluation of biometric fingerprint matchers in a forensic context using latent impressions. In *Proceedings of the on Multimedia and security*, pages 133–138, 2012.

[47] S. Karimi-Ashtiani and C.-C. Kuo. A robust technique for latent fingerprint image segmentation and enhancement. In *International Conference on Image Processing (ICIP)*, pages 1492 –1495, 2008.

[48] M. Kawagoe and A. Tojo. Fingerprint pattern classification. *Pattern Recognition*, 17(3):295 – 303, 1984.

[49] M. Kcken and A. C. Newell. A model for fingerprint formation. *EPL (Europhysics Letters)*, 68(1):141, 2004.

[50] M. Kcken and A. C. Newell. Fingerprint formation. *Journal of Theoretical Biology*, 235:71–83, 2005.

[51] T. Kent. Visualization or development of crime scene fingerprints. In *Encyclopedia of Forensic Sciences*, pages 117 – 129. Academic Press, 2013.

[52] P. Komarinski and Ed. Automated Fingerprint Identification Systems (AFIS). *Elsevier Academic Press*, 2001.

[53] H. C. Lee and R. E. Gaensslen. Methods of latent fingerprint development. *Advances in Fingerprint Technology, second edition, CRC Press*, pages 105–175, 2001.

[54] E. Liu, S. Arora, K. Cao, and A. K. Jain. A feedback paradigm for latent fingerprint matching. In *6th IAPR International Conference on Biometrics (ICB)*, 2013.

[55] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar. *Handbook of fingerprint recognition, 2nd edition*. Springer-Verlag, 2009.

[56] R. Merkel, J. Dittmann, and C. Vielhauer. How contact pressure, contact time, smearing and oil/skin lotion influence the aging of latent fingerprint traces: First results for the binary pixel feature using a CWL sensor. In *IEEE International Workshop on Information Forensics and Security (WIFS)*, pages 1–6, 2011.

[57] A. Mikaelyan and J. Bigun. Ground truth and evaluation for latent fingerprint matching. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 83–88, 2012.

[58] J. L. Mnookin. The validity of latent fingerprint identification: confessions of a fingerprinting moderate. *Law, Probability and Risk*, 7:127, 2008.

[59] A. Nagar, H.-S. Choi, and A. K. Jain. Evidential value of automated latent fingerprint comparison: An empirical approach. *IEEE Transactions on Information Forensics and Security*, 7(6):1752 –1765, 2012.

[60] K. Nandakumar, Y. Chen, S. Dass, and A.K.Jain. Likelihood ratio based biometric score fusion. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(2):342 –347, 2008.

[61] M. Olsen, H. Xu, and C. Busch. Gabor filters as candidate quality measure for NFIQ 2.0. In *5th IAPR International Conference on Biometrics (ICB)*, pages 158–163, 2012.

[62] S. Pankanti, S. Prabhakar, and A. K. Jain. On the individuality of fingerprints. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(8):1010 – 1025, 2002.

[63] S. Patel. Fingerprint Verification System (FVS), 2012. *Available: http://fvs.sourceforge.net*.

[64] A. Paulino, J. Feng, and A. K. Jain. Latent fingerprint matching using descriptor-based hough transform. In *International Joint Conference on Biometrics (IJCB)*, 2011.

[65] A. A. Paulino, J. Feng, and A. K. Jain. Latent fingerprint matching using descriptor-based hough transform. *IEEE Transactions on Information Forensics and Security*, 8(1):31 –45, 2013.

[66] A. A. Paulino, A. K. Jain, and J. Feng. Latent fingerprint matching: Fusion of manually marked and derived minutiae. In *23rd Conference on Graphics, Patterns and Images*, SIBGRAPI, pages 63–70, 2010.

[67] G. PHILIPPE, L. Gratie, and S. Kesavan. On the generalized von kármán equations and their approximation. *Mathematical Models and Methods in Applied Sciences*, 17(04):617–633, 2007.

[68] M. Puertas, D. Ramos, J. Fierrez, J. Ortega-Garcia, and N. Exposito. Towards a better understanding of the performance of latent fingerprint recognition in realistic forensic conditions. In *International Conference on Pattern Recognition (ICPR)*, pages 1638–1641, 2010.

[69] A. Sankaran, T. I. Dhamecha, M. Vatsa, and R. Singh. On matching latent to latent fingerprints. In *International Joint Conference on Biometrics (IJCB)*, 2010.

[70] A. Sankaran, M. Vatsa, and R. Singh. Hierarchical fusion for matching simultaneous latent fingerprint. In *International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, 2012.

[71] M. Schott, R. Merkel, and J. Dittmann. Sequence detection of overlapping latent fingerprints using a short-term aging feature. In *IEEE International Workshop on Information Forensics and Security (WIFS)*, pages 85–90, 2012.

[72] H. Seidenberg-Kajabova, V. Pospisilova, V. Vranakova, and I. Varga. An original histological method for studying the volar skin of the fetal hands and feet. *Biomedical Papers of the Medical Faculty of the University Palack*, 154(3):211–218, 2010.

[73] S. Shapoori and N. Allinson. GA-Neural approach for latent finger print matching. In *International Conference on Intelligent Systems, Modelling and Simulation (ISMS)*, pages 49–52, 2011.

[74] N. Short, M. Hsiao, A. Abbott, and E. Fox. Latent fingerprint segmentation using ridge template correlation. In *International Conference on Imaging for Crime Detection and Prevention (ICDP)*, pages 1–6, 2011.

[75] G. Sodhi and J. Kaur. Powder method for detecting latent fingerprints: a review. *Forensic Science International*, 120(3):172 – 176, 2001.

[76] C. Su and S. Srihari. Latent fingerprint core point prediction based on Gaussian processes. In *20th International Conference on Pattern Recognition (ICPR)*, pages 1634 –1637, 2010.

[77] M. K. Taylor, W. Chapman, A. Hicklin, G. Kiebuzinski, P. Komarinski, J. Mayer-Splain, and R. Wallner. Latent Interoperability Transmission Specification, LITS. *http://www.nist.gov/manuscript-publication-search.cfm?pub_id=913170*, 2013.

[78] R. B. Thompson and B. F. Thompson. Illustrated guide to home forensic science experiments. *O'Reilly Media, Make*, 2012.

[79] B. Ulery, R. Hicklin, J. Buscaglia, and M. Roberts. Accuracy and reliability of forensic latent fingerprint decisions. *Proceedings of the National Academy of Sciences*, 108(19):7733–7738, 2011.

[80] B. T. Ulery, R. A. Hicklin, J. Buscaglia, and M. A. Roberts. Repeatability and reproducibility of decisions by latent fingerprint examiners. *PLoS ONE*, 7:e32800, 03 2012.

[81] B. T. Ulery, R. A. Hicklin, G. I. Kiebuzinski, M. A. Roberts, and J. Buscaglia. Understanding the sufficiency of information for latent fingerprint value determinations. *Forensic Science International (In press)*, 2013.

[82] M. Vatsa, R. Singh, A. Noore, and S. Singh. Quality induced fingerprint identification using extended feature set. In *IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pages 1–6, 2008.

[83] R. Vazan. SourceAFIS, 2012. *http://sourceforge.net/projects/sourceafis*.

[84] G. Warner. Practical fingerprint analysis process and challenges both internal and external for the latent print community. In *IEEE Conference on Technologies for Homeland Security (HST)*, pages 384–389, 2012.

[85] D. Warrington. Developing and lifting latent fingerprints off unusual and textured surfaces. *Manual handout sponsored by Lynn Peavey Company*.

[86] C. Wilson. Fingerprint Vendor Technology Evaluation 2003: Summary of Results and Analysis Report, NISTIR 7123. *http://fpvte.nist.gov/report/ir_7123_analysis.pdf*, 2004.

[87] B. Yamashita and M. French. Fingerprint Sourcebook - Chapter 7: Latent Print Development. *Technical reports, National Institute of Justice - NCJRS*, 2010.

[88] S. Yoon, J. Feng, and A. Jain. Latent fingerprint enhancement via robust orientation field estimation. In *International Joint Conference on Biometrics (IJCB)*, pages 1 –8, 2011.

[89] S. Yoon, J. Feng, and A. K. Jain. On latent fingerprint enhancement. *SPIE Biometric Technology for Human Identification*, 2010.

[90] S. Yoon, E. Liu, and A. K. Jain. On latent fingerprint image quality. In *International Conference on Pattern Recognition (ICPR) IWCF Workshop*, Nov. 2012.

[91] J. Zhang, R. Lai, and C.-C. Kuo. Latent fingerprint segmentation with adaptive total variation model. In *5th IAPR International Conference on Biometrics (ICB)*, pages 189–195, 2012.

[92] J. Zhang, R. Lai, and C.-C. J. Kuo. Latent fingerprint detection and segmentation with a directional total variation model. In *19th IEEE International Conference on Image Processing (ICIP)*, pages 1145–1148, 2012.

[93] Q. Zhao and A. Jain. Model based separation of overlapping latent fingerprints. *IEEE Transactions on Information Forensics and Security*, 7(3):904 –918, 2012.