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Latent Fingerprint Matching Using Grey Level Co-Occurrence Matrix

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Abstract: *Recognizing defendant based on impressions of fingers from crime scenes is important to law enforcement agencies. Latents are partial fingerprints with small area, contain nonlinear distortion,and are usually dirty and less distinct. Due to some of these characteristics, they have a seriously smaller number of minutiae points and thus it can be distinctly difficult to automatically match latents to plain or rolled fingerprints that are stored in law enforcement databases. The goal is to develop a latent matching algorithm that uses only minutiae information. The proposed algorithm uses a robust alignment algorithm (descriptor-based Hough transform) to align fingerprints and measures similarity between fingerprints by considering both minutiae and orientation field information.Since the proposed algorithm depend only on manually marked minutiae, it can be easily used in the law enforcement application.We can added an texture feature to improve the matching performances by using a method called gray-level co-occurrence matrix.The texture features are contrast,correlation,energy and homogeneity.The proposed approach consists of following three modules: (i) align two sets of minutiae by using a descriptor-based Hough Transform; (ii) establish the correspondences between minutiae; and (iii) compute a similarity score.*
Keywords**:** *Fingerprints; Hough Transform; Latents; Minutiae; Matching*

I. Introduction

The practice of identifying suspects using latent fingerprint is not new. Law enforcement Agencies have started using fingerprint technology to identify suspects since the early 20th century. No two individuals will have same fingerprints made many law enforcement agencies aware of the potential of using fingerprints as a means of identification.Fingerprint recognition started as a completely manual Approach. Growing demands on fingerprint recognition, initiated a research to automate fingerprint recognition, which developed an Automated Fingerprint Identification Systems (AFIS).These systems are used worldwide such as in law enforcement agencies, many other government and commercial applications. Today fingerprint recognition is consistently used in civilian applications that have stringent security requirements

There are three categories of fingerprint in Biometrics forensic application (a) Roll fingerprint, which fingerprint image are obtained by Rolling a finger from one side to the other nail to nail in order to capture all ridge details of a finger. (b) Plain fingerprint which are plain fingerprint which are plain impression are those in which the finger is pressed down on flat surface but cannot Latents inadvertently Handled by crime scenes (Latents print). Rolled and plain fingerprints are also called full finger prints.Fig 1 shows different fingerprint.

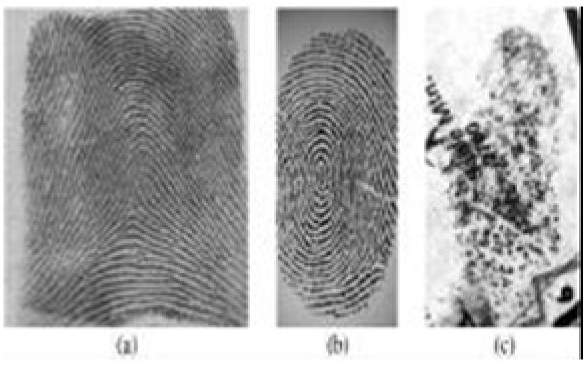

Fig.1 Three types of fingerprint impressions. (a) Rolled; (b) plain; (c) latent

Rolled fingerprints contain the largest amount of information since they contain information from nail-to-nail; latents typically contain the least amount of information for matching or identification. Latents capture only a small finger area.They are smudgy and blurred, and have large nonlinear distortion due to pressure variations. Due to their deprived quality and small area, latents have a drastically smaller number of minutiae compared to full prints. That uniqueness makes the latent fingerprint matching problem very tricky.

Manual latent fingerprint identification is performed following a procedure referred to as ACE-V which involves Analysis, Comparison, Evaluation and Verification. This procedure is quite tedious and time consuming for latent examiners, and requires a large amount of human intervention. Latents are generally matched against full prints of a small number of suspects. With the invention of AFIS, fingerprint examiners identify latents using a semi-automatic procedure that consists of following stages: (i) manually mark the features in the latent, (ii) launch an AFIS search, and (iii)
visually verify each of the candidate fingerprints returned by AFIS. The accuracy and speed of this procedure is not satisfactory. Fig.2 shows three latents of different quality.

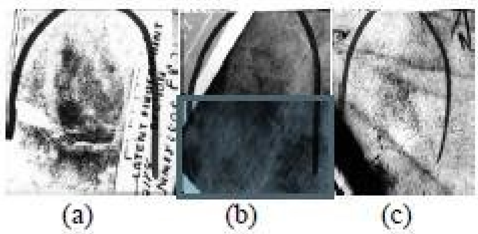

Fig.2 Latent fingerprints of three different quality levels. (a) Good; (b) bad; (c) ugly

The objective is to develop a latent fingerprint matching algorithm that is solely based on minutiae and also to obtain higher matching accuracy. Since physically marking of minutiae in latents is a common practice in the latent fingerprint community.

There are two problems can be solved for fingerprint matching.The problem is align the two fingerprints can be compared and the second one is compute a match score between the two fingerprints. Latents often contain a small number of minutiae and undergo large skin distortion.Due to these reasons alignment between latent and rolled is an challenging problem. To deal with these two problems, we propose the descriptor-based Hough transform (DBHT).It is a combination of the generalized Hough transform and a local minutiae descriptor, called Minutia Cylinder Code (MCC).[2]

II. Related Works

In this section, we review related work in four areas: published research on full fingerprint matching1, published research on latent fingerprint matching, evaluation of latent fingerprint technologies (ELFT), and evaluation of latent examiners

A. Full Fingerprint Matching

Minutiae information is used in most of the algorithms to match fingerprints. Although, Minutiae hold a great amount of unfair details; in some cases added features may increase the accuracy. Most of the proposed algorithms for fingerprint matching that uses non-minutiae features also use minutiae information. Local minutiae descriptors are used to achieve the alignment between two fingerprints by considering the most similar minutiae pair in the initial step; obtaining a better matching performance is the next step.

B. Latent Fingerprint Matching

Latest research and development efforts on latent fingerprints can be broadly classified into three streams according to the manual input requisite from fingerprint examiners: reliable with existing practice, ever-increasing manual input, or dropping manual input. Because of great variations in latent fingerprint eminence and specific requirements of practical applications, each of the three streams has its mark. Enhanced latent matching accuracy has been resulted by using extended features, which are manually marked for latents [3].

Nevertheless, marking extended features (orientation field, ridge skeleton, etc.) in deprived quality latents is very time-consuming and might be only possible in rare cases Therefore, some studies have concentrated on latent matching using a condensed amount of manual input, i.e., region of interest (ROI) and singular points which are marked manually. Thus, only a minute portion of latents can be properly identified using this method. Thus our projected matcher takes manually marked minutiae as input and, therefore, it is reliable among existing practice. There are some developments on fusion of multiple matchers [11] or multiple latent prints [9].In the ACE-V practice, the examiner analyzes the latent image visually and they decide whether the latent has value for exclusion, individualization or no value. If a latent is given as of no value, comparison is not performed. If the latent has a value, then comparisons are performed and the examiners can make individualization, exclusion, or determine the comparison to be uncertain. So the latents which are successfully identified constitute only a small part of all latents, which are of rational quality.

C. Evaluation of Latent Fingerprint Technologies

NIST has been conducting a multi-phase project on Evaluation of Latent Fingerprint Technologies (ELFT).The purpose of ELFT is to evaluate latent feature extraction and matching techniques [23]. The Automated Feature Extraction and Matching (AFEM) is used for assess the feasibility of latent fingerprint identification systems.This is the purpose of ELFT-Phase 1. While the purpose of ELFT-Phase II was to measure the performance of state-of-the-art AFEM technology.

Another properties of Phase II is to evaluate whether it was viable to have those systems in the operational use to reduce the amount of time needed by latent examiners to manually mark latents thereby increasing the throughput. Latent images were selected from both operational and non-operational scenarios in Phase I. The rank-1 accuracy of the most accurate system was 80%(100 latents against 10, 000 rolled prints) [5]. In Phase II, latent images were selected from only operational environments. The rank-1 accuracy of the most accurate system was 97.2% (835 latents against 100, 000 rolled prints) [6].The Phase I and Phase II evaluations used different latent databases so these accuracies cannot be directly compared. The quality of latents used in Phase II is better than Phase I.

The impressive matching accuracy reported in ELFT does not support that the current practice of manually marking minutiae in latents should be changed. In Phase II latents were selected from operational scenarios.So they represent successful identifications in actual case examinations using existing AFIS technology.

In the ACE-V process, when the examiner analyzes the latent image he/she decides whether the latent has value for exclusion only, value for individualization or no value. If a latent is classified as of no value, no comparison is performed. If the latent is classified in one of the other two categories, then comparisons are performed and the examiners can make an individualization, an exclusion, or determine the comparison to be inconclusive. So the latents which are successfully identified constitute only a small part of all latents, which are of reasonable quality. For this reason, in the ELFT-Phase II report [10] we can concluded that only a limited class of latents can benefit from AFEM technology.

NIST has conducted another evaluation of latent fingerprint technologies using extended feature sets manually marked by latent examiners [8]. In this evaluation, the purpose was to investigate the matching accuracy when (i) latent images and/or (ii) sets of manually marked features were provided. This evaluation suggested that the highest accuracy was obtained when the input included both the latent image and manually marked features.

D. Evaluation of Latent Examiners

A latent examiner may be a slow but very precise "matcher". They are comparatively slower than automatic matchers, so quantitatively estimating the accuracy of latent examiners is not so easy. It was found that latent examiner's conclusions are not always in agreement, in particular in the case of poor quality latents. In addition, the same examiner can change his/her conclusions on the same fingerprint pair at a later on time. These inconsistencies may increase in bias.When the automatic matcher can outperform latent examiners in accuracy all the issues associated with including latent examiners in the latent identification process will be solved. No matter how successful the application of automatic fingerprint recognition technology might be, before we can reach the goal of outperforming latent examiners we cannot say fingerprint matching is a "solved problem".

III. Proposed System

There are three main steps in fingerprint matching: alignment of the fingerprints, pairing of the minutiae, and score computation. In our approach, we use a Descriptor based Hough Transform to align two fingerprints. Fig.3 shows an overview of the proposed approach. It is important to emphasize that while latents are manually encoded (namely marking minutiae); minutiae in rolled prints are automatically extracted.

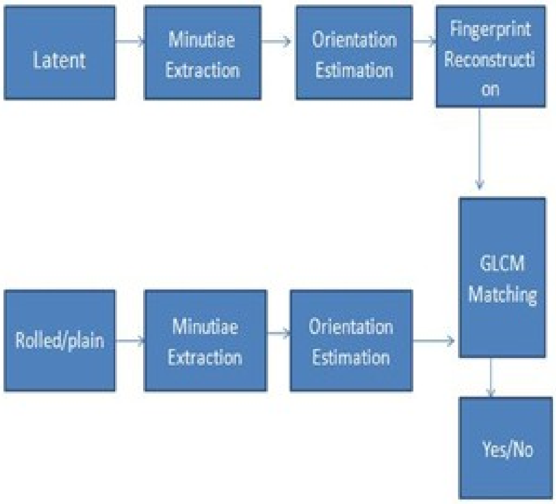

Fig.3 Overview of the proposed approach

A. Feature Extraction

The proposed matching approach uses minutiae and orientation field from both latent and rolled prints. Minutiae are manually marked by latent examiners in the latent, and automatically extracted using commercial matchers in the rolled print. Based on minutiae, local minutiae descriptors are built and used in the proposed descriptor-based alignment and scoring algorithms. Orientation field is reconstructed from minutiae location and direction for the latents as proposed in [30], and orientation field is automatically extracted from the rolled print images by using a gradient-based method.
Local minutia descriptors and orientation field reconstruction are presented in the following subsections.

1. Local Minutia Descriptor

Minutia Cylinder-Code (MCC) is a minutiae representation based on 3D functions . In the MCC representation, a local structure is associated toward each minutia, where this local structure is represented as a cylinder, which contains information about the relationship between two adjoining minutiae. The base of the cylinder is related to the spatial relationship, and its height to the directional relationship. Every cell in the cylinder accumulates help from each minutia in the neighborhood. The resulting cylinder is concatenated as a vector, and so the similarity between two minutia descriptors can be effectively computed as a vector correlation measure. This representation has some advantages,Such as: invariant to translation and rotation; robust against small skin distortion and missing or spurious minutiae; and of fixed length.

2. Orientation Field Reconstruction

In several ways orientation field can be used to improve fingerprint matching performance, such as by matching orientation fields directly and fusing scores with other matching scores, or by enhancing the images to extract more reliable features.In good quality images orientation field estimation can be done using gradient–based method.It is reliable method.[7]. If the image contains noise, this estimation becomes very challenging. A few model based orientation field estimation methods use singular points as input to the model. In the latent fingerprint matching case, it is very challenging.Because estimate the orientation field based only on the image due to the poor quality and small area of the latent. Moreover, if singular points are to be used, they need to be manually marked in the latent fingerprint image. Hence, we use a minutiae-based orientation field reconstruction algorithm.In this [4] takes input as manually marked minutiae in latents and outputs an orientation field. This approach estimates the local ridge orientation in a block by averaging the direction of neighboring minutiae. The orientation field is reconstructed only inside the convex hull of minutiae. Since the direction of manually marked minutiae is very reliable, the orientation field reconstructed using this approach is quite accurate except in areas absent of minutiae or very close to singular points. By using a gradient-based method orientation field is automatically extracted in rolled fingerprints.[7].

B. Alignment

Fingerprint alignment involves estimating the parameters (rotation, translation and scale) that align two fingerprints. A number of features may be used to estimate alignment parameters between two fingerprints, including orientation field, ridges and minutiae. Generalized Hough Transform, local descriptors, energy minimization are the various methods to align two fingerprints.

In the latent fingerprint matching, singularities are not present always, making it difficult to base the alignment of the fingerprint on singular points only. To attain manually marked orientation field is expensive, and to extract orientation field from a latent image automatically is very challenging. Since manual marking of minutiae is a universal practice for latent matching, our advance to line up two fingerprints is based on minutiae.

An alignment process for minutiae matching which estimates parameters like scale, rotation, and translation by using a Generalized Hough Transform is introduced in [9]. Given two sets of points (minutiae), a matching score is computed for each transformation in the discretized set of all allowed transformations. For every pair of minutiae, one minutia from each image, and for given scale and rotation parameters, exclusive translation parameters can be computed. Each parameter receives "a vote" relative to the matching score for the corresponding transformation. The transformation that gives the greatest score is considered as the best. In our approach, the alignment is done in a very similar way, but the evidence for each parameter is accumulated based on the similarity among the local descriptors of the two involved minutiae, with the correspondence and descriptor being the ones described in the local minutiae descriptor.

Given two sets of minutiae to compare, one from the latent print and the other from the rolled print. Rotation and translation parameters can be achieved for every possible minutiae pair (one minutia from each set). Let {(xl , yl , Θl)}and {(xr , yr , Θr)} be the minutiae sets for latent and rolled prints centered at their means respectively. Then, for every minutiae pair, we have

$$\theta = min(\|\theta_l - \theta_r\|, 360 - \|\theta_l - \theta_r\|)$$

$$\begin{pmatrix}\Delta x\\ \Delta y\end{pmatrix} = \begin{pmatrix}x_r\\ y_r\end{pmatrix} - \begin{pmatrix}cos\theta & sin\theta\\ -sin\theta & cos\theta\end{pmatrix}\begin{pmatrix}x_1\\ y_1\end{pmatrix}$$

Since it is not essential to consider the scale parameters in fingerprint matching, translation parameters can be achieved uniquely for each pair depending on the rotation difference between the paired minutiae. The parameters of translation and rotation are quantized to their neighboring bins. Once quantized, evidence is accumulated in the corresponding bin based on the similarity between the local minutiae descriptors. The assumption is that true mated minutiae pairs will vote for very similar sets of alignment parameters, while non-mated minutiae pairs will vote randomly throughout the parameter space. Thus, the set of parameters that presents the highest evidence is considered the best. For robustness,more than one set of alignment parameters with high evidence are to be considered. In order to make the alignment more accurate and computationally efficient, a two stage approach for the Descriptorbased Hough Transform is used. We first perform the voting in a relatively common parameter space. Based on the peaks in the Hough space, we replicate the voting inside a neighborhood around the peaks, but with a more advanced set of parameter range. Then keep track of the points that contribute to the peaks and compute a rigid transformation matrix from those points.

After the alignment of two sets of minutiae, we need to find the minutiae correspondences between the two sets, i.e.minutiae which need to be paired. The pairing of minutiae consists of finding minutiae that are suitably close in terms of location and direction. Let mi = (xi,yi,Θi) be a minutia from the aligned latent and mj = (xj,yj,Θj) be a minutia from the rolled print. Then, mi and mj are considered paired or matched minutiae if

$$d(m_i, m_j) = \sqrt{((x_i - x_j)^2 + (y_i - y_j)^2\ )} \le d_0$$

$$\theta_{ij} = min(\|\theta_i - \theta_j\|, 360 - \|\theta_i - \theta_j\|) \le \theta_0$$

In aligning two sets of minutiae, we use a one-to-one matching; this is the most natural way of pairing minutiae.

Which means each minutia in the latent can be matched to only one minutia in the rolled print. Ties are broken depends on the closest minutia.

C. Score Computation

Score computation is a very essential step in the matching process. A straight approach to compute the matching score consists of the number of matched minutiae divided by the average number of minutiae in the two finger- prints. This is not appropriate for latent matching because the number of minutiae in different latents varies significantly. One solution to modify the above said scoring method is to divide the number of matched minutiae by the number of minutiae in the latent, which is almost always smaller than the number of minutiae in the rolled fingerprint.

To compute minutiae matching score under a given alignment, we first find the corresponding minutiae pairs (one in the latent, one in the rolled print). For this purpose, we align the minutiae sets of the two fingerprints and then find an one-to one matching between the two minutiae sets using a greedy algorithm. For each minutia ml in the latent, a set of candidate minutiae in the rolled print is found. A minutia mr in the rolled print is called a candidate if it has not yet been matched to any minutia, and both its location and angle are sufficiently close to ml. The threshold values TS for spatial distance and TA for angle distance were determined empirically. Among all candidates, the one closest to ml in location is chosen as the matching minutia of ml. After the corresponding minutiae are found, we compute a matching score between the latent and the rolled print. Suppose that n pairs of matching minutiae between the latent and the rolled print are found. The minutiae matching score SM between the two fingerprints is given by

$$S_{\mathrm{M}} = \frac{1}{N}\sum_{i=1}^{n} s_{\mathrm{C}}(i)s_{\mathrm{S}}(i),$$

To further improve the matching performance, combine the scores based on matched minutiae from two different pairing thresholds by their weighted sum; assume equivalent weights. As we perform 10 different alignments, we compute 10 different scores between two fingerprints; the final score between the two fingerprints is the maximum among the 10 scores computed from dissimilar hypothesized alignments.

IV. Solution Methodology

The descriptor-based Hough transform alignment algorithm takes as input two sets of minutiae, ML and MR, and two sets of local descriptors CL and CR, one set corresponding to the latent and one to the rolled print. Each set contains a local descriptor for each minutia. A high level algorithm of the proposed approach to align two fingerprints given the sets of minutiae and of local descriptors is shown in Algorithm .

Input: {ml} = {(xl, yl, Θl)} 2 ML, {mr} = {(xr, yr, Θr)} ϵ

MR, CL, and CR

Output: A set of 10 rigid transformation matrices

Initialize the accumulator array A

Compute local minutiae descriptor similarity (W) for every possible minutiae pair using CL and CR

for all possible pair ml, mr **do**

Compute their direction difference ΔΘ = (Θr − Θl) **if** ΔΘ < maxΘ **then**

Compute translation parameters (Δx,Δy) and increase the voting for this set of alignment parameters:

A(Δx, Δy, ΔΘ) = A(Δx, Δy, ΔΘ) +W(l, r) **end if**
end for

Smooth A using a Gaussian low-pass filter Find 10 highest peaks in A

for each peak k **do**

Compute a rigid transformation between two fingerprints using minutiae pairs that contributed to peak k and its immediate neighborhood

if the estimated rigid transformation is not reliable **then**

Repeat the voting in peak k and its neighborhood using a refined range

Find the highest peak in the small neighborhood of peak k **end if**

end for
Gray-level co-occurrence matrix

Gray-level co-occurrence matrix technique of fingerprint recognition using a set of texture based features. The proposed approach utilizes three texture based feature for recognizing fingerprint classes viz contrast,Homogenity, 2Dcorrelation coefficient and energy of wavelet coefficients.Each of these four features are represented as scalar values.

An image of GLCM (i ,j) extracts the features based on pixel and its next neighbour pixel in the image. GLCM (i, j) is a two dimensional function and it is composed of m pixels in the vertical direction and n pixels in the horizontal direction, i, j are horizontal and vertical co - ordinates of the image. The total number of pixels in the image is m*n = N, 0<=i<=m ,0 <=j<=n.

Firstly, the intensity contrast between a pixel and its neighbour is determined over an entire image. It is known that the similar values of pixels in observation results in low contrast causing a poor dissemination of boundaries between features. This contrast intensity is calculated with the equation

$$\text{Contrast: } \Sigma_{i=1}^{M} \Sigma_{j=1}^{N} (i-j)^2 GLCM(i,j) \qquad (1)$$

Similarly the textural uniformity is obtained with equation

(2) as statistical measure energy. This infers that maximum constant values or periodic uniformity in gray level distribution will form maximum energy of texture. Clear domain of group of textures is deciphered on account of higher value in energy measure.

$$\text{Energy: } \Sigma_{i=1}^{M} \Sigma_{j=1}^{N} (GLCM(i,j))^2 \qquad (2)$$

The closeness of gray levels in the spatial distribution over image is inferred by homogeneity.Homogeneous textured image is comprised of limited range of gray levels and hence, the GLCM image exhibits a few values with relatively high probability .

Correlation that brings out how correlated a reference pixel to its neighbor over an image, is uncorrelated to energy, contrast and homogeneity.

V. Conclusion And Future Work

The latent fingerprints are found at law enforcement agencies crime sense. The fingerprint matching for matching latents rolled finger prints and plain finger prints. Due to its poor/ bad quality images. It is use to different enhance process to obtaining the clear ridge orientation field.The proposed alignment technique performs very well even on latent's that contain small number of minutiae. In our algorithm, maximum score is considered from several hypothesized alignments based on different alignment parameters. Sometimes, the maximum score does not correspond to the correct alignment. We plan to add a texture-based descriptor can be included to improve the matching accuracy especially when the overlap area between the latent and rolled prints is small.

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References

[1]. A. A. Paulino, J. Feng, and A. K. Jain, "Latent fingerprint matching using descriptor-based Hough transform," in Int'l Joint Conf. on Biometrics, October 2011, pp. 1–7

[2]. R. Cappelli, M. Ferrara, and D. Maltoni, "Minutia cylinder-code: a new representation and matching technique for fingerprint recognition," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 32, no. 12,pp. 2128–2141, December 2010.

[3]. Jain.A.K, J.Feng, Nagar, Nandakumar k "On matching latent fingerprints," 2008 CVPR Workshop on biometrics.

[4]. J. Feng and A. K. Jain, "Fingerprint reconstruction: from minutiae to phase," IEEE Trans. on Pattern Analysis and Machine Intelligence,vol. 33, no. 2, pp. 209–223, February 2011.

[5]. X. Jiang, M. Liu, and A. C. Kot, "Fingerprint retrieval for identification,"IEEE Trans. on Information Forensics and Security, vol. 1, no. 4, pp.532–542, December 2006

[6]. R. Cappelli, M. Ferrara, and D. Maltoni, "Minutia cylinder-code: a new representation and matching technique for fingerprint recognition," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 32, no. 12,pp. 2128–2141, December 2010

[7]. D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, Handbook of Fingerprint Recognition, 2nd ed. Springer-Verlag, 2009.

[8]. M. Indovina, R. A. Hicklin, and G. I. Kiebuzinski, "NIST evaluation of latent fingerprint technologies: Extended feature sets [Evaluation #1]," NIST Interagency/Internal Report (NISTIR) - 7775, Tech. Rep., April 2011

[9]. X. Chen, J. Tian, and X. Yang, "A new algorithm for distorted fingerprints matching based on normalized fuzzy similarity measure," IEEE Trans. on Image Processing, vol. 15, no. 3, pp. 767–776, March 2006.

[10]. M. Indovina, V. Dvornychenko, E. Tabassi, G. Quinn, P. Grother S. Meagher, and M. Garris, "An evaluation of automated latent fingerprint identification technology (Phase II)," NIST Interagency/Internal Report (NISTIR) - 7577, Tech. Rep., April 2009A.Sankaran, T. I. Dhamecha, M. Vatsa, and R. Singh, "On matching latent to latent fingerprints," in Int'l Joint Conf. on Biometrics, October 2011, pp. 1–6.

[11]. M. Vatsa, R. Singh, A. Noore, and K. Morris, "Simultaneous latent fingerprint recognition," Applied Soft Computing, vol. 11, no. 7, pp. 4260–4266, October 2011