

Latent Fingerprint Recognition using Hybridization Approach of Partial Differential Equation and Exemplar Inpainting

Himanshi, Anit Kaur and Amit Verma

Computer Science and Engineering, Chandigarh Engineering College, Landran, Mohali – 140307, Punjab, India;
kaushalhimanshi28@gmail.com, anit.cse@cgce.edu.in, dramit_verma@yahoo.com

Abstract

Objectives: Biometric based Fingerprint recognition system is one of the well-adapted approaches in online security prospects. However, due to user-friendly behaviour of advanced computing systems, biometric approach is not much in use now days. The approach left its footprints only with the applications to identify criminal activities at crime scenes where fingerprints are mainly available in latent form. Latent fingerprints are the accidentally left finger skin impressions by criminals. These impressions are invisible for the naked human eye and usually captured with lasers, chemical, powders etc. These captured latent fingerprints carries less minutiae information with distorted ridges and high level of pattern overlapping. So, it is not easy to identify the criminals with partial fingerprint information. **Methods/Statistical Analysis:** In this paper, hybrid approach of Exemplar In painting and Partial Differential Equation is used to fill up the distorted ridges. The main goal of this work is to present the framework to reconstruct the latent distorted fingerprint and further use them to find the best match for those enhanced reconstructed latent fingerprints. For the experimentation of proposed hybrid concept, IIIT Delhi latent and NIST SD-27 databases of fingerprint are used. In this experimentation, different fingerprint enhancement filters like Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, Gaussian High Pass Filter are used. **Findings:** Different filters show different performance of dataset images for latent fingerprint recognition. The overall performance of the automated latent fingerprint identification approach is analysed in terms of false acceptance rate and genuine acceptance rate. **Application/Improvements:** In this way, latent fingerprint can be used for the recognition of criminal activities at crime scenes where fingerprints are mainly available in latent form. The overall concept shows better results for canny filter as compare to other considered filters in enhancement.

Keywords: Binarization Approach, Criminal Activities, Exemplar Inpainting, Latent Fingerprint, Minutiae Extraction, Partial Differential Equation

1. Introduction

In today's world, criminal activities are on great hike. So, there is need to design more advanced autonomous methods to catch the criminals¹. Here, latent fingerprints based method is used to find the criminals. Latent fingerprints are the accidentally left finger impressions during the crime scene². These latent fingerprints are not easy to detect, as these are not visible with naked human eye. To collect these latent fingerprints various laser based, chemical and many means that are more physical

can be adapted. These collected latent fingerprints cannot be directly used to find the match with the existing fingerprints repository. A sample of distorted latent fingerprints is shown in Figure 1.



Figure 1. Sample of Latent Fingerprints.

As shown in Figure 1, latent fingerprints are distorted and overlapping fingerprints having less minutiae information and broken curves & ridges. As per the noise level, latent fingerprints are available with background noise, partial fingerprint and overlapping latent. Manual identification of these latent fingerprints is more time consuming and laborious task as it is not easy to capture the each small minutiae in fingerprints. So, there is the need of some autonomous approach that can enhance and reconstruct the latent fingerprints so that the perfect match can be identified.

In this paper, we have presented the framework for the recognition of latent fingerprints³. This fingerprint recognition system consists of three modules (shown in Figure 2) i.e. pre-processing, feature extraction and post-processing.

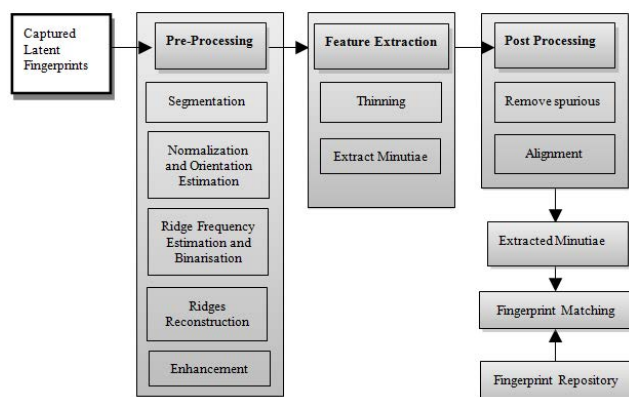


Figure 2. Framework for Latent Fingerprint Recognition.

Initially, crude latent data is considered as input and preprocessing steps are applied to refine the input fingerprints. Pre-processing involves the steps of Segmentation, normalisation & orientation estimation, ridge reconstruction⁴, binarisation and enhancement of latent fingerprints. Segmentation is performed to segment the foreground and background portion of the latent fingerprints. Then latent fingerprints are normalized and their orientation is estimated. The main step is distorted ridge reconstruction by using the hybrid approach of Exemplar Inpainting and Partial Differential Equation⁵. Inpainting approaches are used to fill up the distorted image portion. Here, inpainting approaches are considered to reconstruct the broken ridge structures of latent fingerprints so that they can be use to match with original repository. Further, binarisation is performed to convert the grey level image into a black and white pixels based binary image. These refined latent fingerprints are further

enhanced using the Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, Gaussian High Pass Filter. Different filters are used to attain different features like intensity, edges, ridge etc.

After pre-processing, next module of fingerprint recognition system is Feature Extraction. Feature extraction includes the steps of thinning and minutiae extraction phases. Thinning is performed to separate the overlapping minutiae information using the morphological operations. But due to thinning process some spurious features also comes in original minutiae. Further features are extracted in the form of minutiae and ridge flow from the latent fingerprints.

Finally these latent fingerprints are post-processed. Post processing involves the steps of removal of false minutiae, alignment of fingerprints and matching of extracted features with the fingerprint repository. Due to thinning process some spurious features also comes in original minutiae. So, in post processing false minutiae's are removed so that the relevant and necessary features are stored⁶. Geometrical transform function is used for the alignment of the latent fingerprints. Further, minutiae and pattern of latent fingerprints are matched with the original fingerprints. Final matching is performed with the binarisation approach to get the image in binary pixels format.

Rest of the section is described in the following manner: Section 2 presents the existing work for latent fingerprint identification. Section 3 describes the basic concepts used like Exemplar inpainting, partial differential equation, Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, Gaussian High Pass Filter. Section 4 discusses about the proposed AFIS system. Section 5 brief about the dataset considered for experimentation. Section 6 describes the evaluated results by considering evaluation parameters of FAR & GAR and Section 7 concludes the paper with some future directions.

2. Related Work

In this computing era, researchers are continuously working to enhance the existing AFIS and generate the more autonomous latent fingerprints identification methods. Existing work for the latent fingerprint identification is presented here. Different authors have used different methods for the different modules of latent fingerprint matching.

For the segmentation of the latent fingerprints, existing work is listed here. In⁷, authors have used frequency & orientation tensors and achieves rank-1 identification accuracy of 16.28% in NIST SD-27 and 35.19% in WVU DB database. In⁸, authors have used adaptive total variational model for segmentation but no any evaluation is performed in this approach.

For the quality assessment of latent fingerprints, existing work is presented here. In⁹, authors have presented the ridge clarity maps technique and attains the rank-100 accuracy value upto 86% for the NIST SD-27 and WVU dataset repository. In¹⁰, authors have described a method using color coded annotations to evaluate the clarity of ridge impressions. The author also distinguished clarity from the concept of quality. Hence, low quality regions bear high clarity if there is availability of only few features.

Further for the enhancement of latent fingerprints, existing work is discussed. In¹¹, authors have proposed ridge orientation based methodology using neural network followed by ternarization. The use of neural network has reduced the rate of false minutiae extraction to a great extent. In¹², authors have proposed Separation Algorithm to improve the accuracy of real overlapped latent fingerprint images. There is the reconstruction of overlapping orientation field of fingerprints which is based on the manually marked features like orientation cues, singular point and region of interest. The proposed separation model not only predicts the unknown orientation but it also fixes the errors of orientation field. In¹³, authors proposed orientation field based approach by using prior knowledge for the enhancement of latent and poor quality fingerprints. Here, the database of NIST SD4 is used for dictionary construction, NIST SD14 as a background database, NIST SD27 and Tringhua OLF for evaluation of proposed algorithm. The proposed concept shows efficient results as compare to conventional approaches but it need improvement due to its slow speed and non-efficiency of low quality latent. In¹⁴, authors have proposed enhancement algorithm based on image decomposition and coarse to fine ridge structure directories. The database of NIST SD27 and WVU DB are used. The major drawback of this proposed concept is that this algorithm does not work well for low quality latent. In¹⁵, authors proposed the novel combined form of total variation model and multiscale path based sparse representation method. The proposed algorithm also restores and enhances the corrupted fingerprints along with the removal of structured noise from images.

Feature extraction is performed by some researcher. In¹⁶, authors have used hough transform method and achieves the accuracy identification rank-1 with accuracy value of 54% in NIST SD 27 dataset and 48% in WVU DB. In¹⁷, authors have used stacked denoising sparse autoencoders approach attained accuracy of 33% for NIST SD 27 dataset.

In¹⁸, authors have used the local and global matching technique for the feature matching and attained the accuracy value of 74% for NIST SD-27 database. Further various authors have presenting the Rank K-matching matrices¹⁹ for the MCC descriptor for minutiae, manually & automated extracted minutiae and orientation field & manual minutiae based matching²⁰.

So, different authors have presented different modules for latent fingerprint recognition. The existing work is presented mainly for the dataset of NIST SD 27 latent fingerprint repository. But the considered concepts have not being able to optimize the false acceptance rate. Also the considered concepts does not work well for low quality images. In this paper, we have proposed the complete framework for latent fingerprint identification with the distorted ridge reconstruction using hybrid EI and PDE. The basic concepts considered for the experimentation are discussed in the next section.

3. Basic Concepts

This section describes the basic concepts of Exemplar Inpainting and Partial Differential Equation for the reconstruction of distorted latent fingerprints. Also the filters used for the image enhancement are discussed here.

A. Partial Differential Equation (PDE)

Partial Differential Equation is a inpainting approach which is use to fill up the latent distorted ridge lines with small fissures. Image Inpainting is the process to recover/ fill up the distorted and broken portion of image using the neighbor pixels. Image Inpainting is one of the commonly used approaches in Photoshop for the image retouching. Initially, Partial differential equation approach was used in the application of computer vision and image processing. Gradually computer vision applications get the support from medical field also. On the same time, PDE was further enhanced for the inpainting solutions in computer vision field. So, further exemplar inpainting techniques were proposed.

B. Exemplar Inpainting (EI)

Exemplar Inpainting is a patch based texture synthesis approach used to reconstruct the missing portion of latent image. Exemplar inpainting mainly works based on priority of the gradient scene. Exemplar Inpainting is the combination of texture and inpainting approach where texture based available information is used to recover the distorted latent region using inpainting approach. As there were some limitations in the PDE approach for the void size, smoothness and low frequency data. Exemplar inpainting approach can be applied to fill any size of void and also support high frequency data.

C. Filters

For the enhancement of the latent fingerprints, we have used the various filters like Canny Edge Detection Filter²¹, Prewitt filter²², Laplacian Filter²³, Sobel Filter²⁴, Gaussian Low Pass Filter²⁵, Gaussian High Pass Filter²⁵. Enhancement of latent fingerprints is performed with each filter and final differentiated results are compared. These considered filters with their key feature are shown in Table 1.

Table 1. Basic Concept and Key Features of Considered Filters for Latent Fingerprint Enhancement

Filter's	Description
Canny Edge Detection Filter ²¹	To detect unwanted information and preserve useful information present in latent fingerprint, canny edge detection plays a significant role.
Prewitt filter ²²	It is also used by the operator to calculate the gradient of image intensity at each point
Laplacian Filter ²³	The Laplacian filter is used to measures second spatial derivative of an image. The regions where the intensity keeps on changing rapidly are highlighted by Laplacian filter.
Sobel Filter ²⁴	It is very similar to Prewitt filter. The major difference in between two filters is the coefficients of masks are not fixed and they can be adjusted according to our requirement
Gaussian Low Pass Filter ²⁵	Blurring mask is also called Gaussian Low pass Filter. All the values in blurring mask are positive. The edge content is minimized by Gaussian low pass filter. This filter can increase the smoothening effect in an image.
Gaussian High Pass Filter ²⁵	Derivative Mask is also called Gaussian High pass filter. The edge content is increased by Gaussian high pass filter. If the size of mask increases then edge content also increases.

4. Automatic Fingerprint Identification System

In the current work, AFIS framework is used for the latent fingerprint recognition. The entire framework consists of three modules of fingerprint preprocessing, feature extraction and post processing. The key module of this identification framework is reconstruction of distorted latent fingerprints. For this reconstruction of latent fingerprints, hybrid approach of exemplar inpainting and partial differential equation is used. The main goal of hybridization is to recover the distorted noisy latent fingerprints of each size, frequency and noise level. PDE approach used to recover the distorted ridge alignment and small fissures. So, exemplar inpainting approach can reconstruct the large size distorted fingerprints having high frequency data format.

The complete proposed concept of latent fingerprint identification with modules of pre-processing, feature extraction and post-processing is shown in Figure 3.

A. Pre-processing

Pre-processing involves the steps of fingerprint segmentation, normalization, orientation estimation, ridge frequency estimation, binarization and enhancement.

Step 1 (Segmentation): Segmentation is performed to separate the foreground region of image from the background noisy region. Segmentation of fingerprint image is executed using grey level variance approach for the block wise divided image. The grey level variance for a $W \times W$ block can be calculated by using equation 1.1 below.

$$V(k) = \frac{1}{W^2} \sum_{i=0}^{W-1} \sum_{j=0}^{W-1} (I(i, j) - M(k))^2 \quad (1.1)$$

Where, $V(k)$ is the variance of the block k , $I(i, j)$ is the grey level value for any pixel (i, j) and $M(k)$ is the mean grey value for k block.

If the variance value of block found to be more than global threshold value, then it will be considered as foreground region having useful ridge based information. If variance value found to be less than threshold value, then it will be declared as background region having noise value.

Step 2 (Normalization & Orientation Estimation): After segmentation, the useful image region is normalized

by adjusting the range of grey level values. Normalization is performed to standardize the image intensity values. The image can be normalized by using the equation 1.2.

$$N(i, j) = \begin{cases} M_0 + \sqrt{\frac{[V_0 I(i, j) - M]^2}{V}} & \text{if } I(i, j) > M \\ M_0 - \sqrt{\frac{[V_0 I(i, j) - M]^2}{V}} & \text{Otherwise} \end{cases} \quad (1.2)$$

Where, $N(i, j)$ denoted the normalized grey level value at pixel (i, j) , $I(i, j)$ describes the grey level image value for pixel (i, j) , M is the Mean and V is the variance at pixel (i, j) . M_0 and V_0 are mean and variance values.

Further, Orientation estimation step is executed for the obtained foreground ridges. For this gradient based approach is used to estimate the orientation of fingerprint image.

Step 3 (Ridge Frequency Estimation): Ridge frequency estimation is also an important step in latent fingerprint recognition. Ridge frequency estimation evaluate the local frequency of ridges which is further used to select the type of filter for enhancement.

Step 4 (Binarization): Binarization of latent fingerprint image converts the grey level (upto 256) image into binary color combination image. Binarisation of image also reduces the background noise level as image pixels remains in black and white color combination based image. During binarisation some ridges and curves also gets distorted.

Step 5 (Reconstruction of Ridges and Curves): For the reconstruction of distorted edges and curves, hybrid approach of partial differential equation and exemplar inpainting approach is used. Partial differential equation uses the gradient of laplacian and recovers the broken curves based on laplacian height values.

Further, patch priority based Exemplar Inpainting approach is used to recover the large distorted ridges and curves. The patch priority depends upon the already filled regions. So, highest patch priority will be either at the corner of target region or at the region having strong ridges in continuation form. Then Euclidean distance is evaluated to find the distance between the source and target region using the equation 1.3.

$$D = \sqrt{\sqrt{x_1 - x_2} + \sqrt{y_1 - y_2}} \quad (1.3)$$

After selecting the highest patch priority based region

and evaluating the distance between the source and target region, distorted regions are filled with the present surrounded information. In this way, all the distorted ridges and curves are recovered using hybrid PDE and EI approach.

Step 6 (Enhancement): As the ridge frequency estimation value, filters are selected for the enhancement of latent fingerprints. In this research work, we are using Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, Gaussian High Pass Filter for the enhancement of latent fingerprints. Different features of different filters are discussed in Table 1.

In this way, all the image pre-processing steps performed with different filters for the enhancement of latent fingerprint image.

B. Feature Extraction

Feature Extraction involves the steps of Thinning and minutiae extraction.

Step 1 (Thinning): Thinning is the morphological process used to erodes the foreground image pixels upto the extent that each pixel gets separately thin. As thinning process sensitive to noise, so there may be chances to extract spurious minutiae from thinned image. In this research work, MATLAB based 'bwmorph' function is used.

Step 2 (Minutiae Extraction): In this research work, basic minutiae extraction approach is used. Here, binarisation based image is considered for the minutiae extraction. Minutiae are extracted from the ridge bifurcation and ridge endings. The accuracy of the latent fingerprint approach is directly proportional to the probability of minutiae extraction.

C. Post processing

Post processing involves the steps of spurious minutiae removal, alignment and matching process.

Step 1 (Remove Spurious Minutiae): As thinning is sensitive to noise value. So, it generally capture some false minutiae information. So, before the final alignment or matching of the fingerprint, these false minutiae's are removed from the data.

Step 2 (Alignment): Before the final matching of the latent fingerprints, images should be proper aligned based on the minutiae information. For the alignment of the fingerprints, geometrical transformation feature which is a MATLAB based inbuilt feature.

Step 3 (Matching): Final step is the matching of the

processed latent fingerprints with the available fingerprints repository images. For this, binarization method is used by converted the image into binary string. For the processed image and stored images, AND operation is performed to find the match. Match value may vary from 0 to 1. More the value near to 1, more accurate results will be.

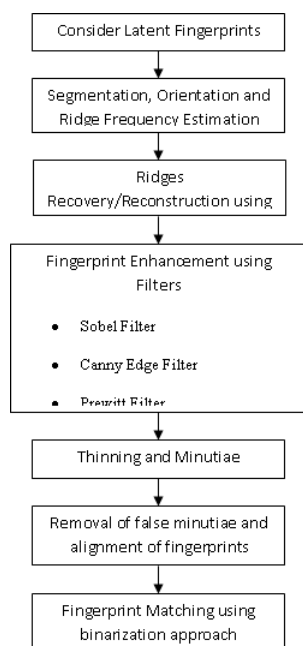


Figure 3. Work Flow for fingerprint Matching.

5. Dataset Considered

The proposed concept is experimented with latent fingerprint dataset of IIIT Delhi and NIST SD-27. IIIT Delhi latent fingerprint dataset consist of 1046 images. Latent fingerprints are lifted using black powder duster process and captured directly using the camera³. Latent fingerprints with mated 500 PPI & 1000 PPI exemplars, slap images of 500 PPI.

NIST SD-27 consists of latent to rolled fingerprints. These images are of 500 PPI and 1000 PPI exemplars. In this dataset, manually annotated features are also available³.

6. Experimental Results and Discussion

This section evaluates the performance of the proposed AFIS for the recognition of latent fingerprints. For this experimentation, MATLAB simulation software is used.

System to operate this tool have window based operating system with an Intel(R) Core(TM) i3 CPU and 4GB RAM. For overall evaluation of implemented concept, parameters of False Acceptance Rate and Genuine Acceptance Rate are considered.

A. Analysis with IIIT D latent fingerprint Dataset

Initially an image is considered from the dataset as shown in Figure 4 (a). To extract the minutiae information, distorted regions are marked manually so that they can be recovered (shown in Figure 4 (b)). Then further hybrid PDE and EI approach is applied to fill up/recover the distorted region. The restored image is shown in Figure 4 (c). To find the best match of the image, image is further enhanced using Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, Gaussian High Pass Filter. With different filter image quality is enhanced but for the different regions. So, further output for minutiae extraction is also changes as the enhancement filter changes. The enhanced image and minutiae extraction features for different filters is shown in Figure 5 (a) (b) to Figure 10 (a) (b).

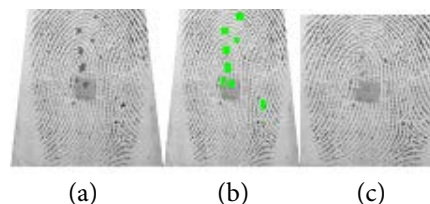


Figure 4. (a). IIIT D latent dataset Input Image, 4(b). Manual marking of distorted regions, 4(c). Recovered image using hybrid PDE and EI approach.

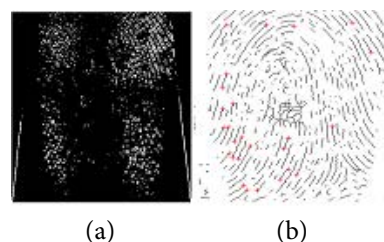


Figure 5. (a). Enhanced Image using Sobel Filter, 5(b). Minutiae Extraction phase.

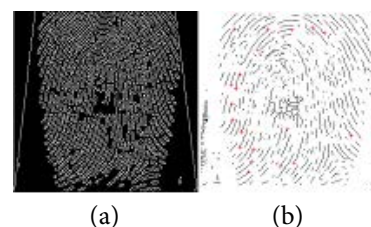


Figure 6. (a). Enhanced Image using Canny Edge Filter, 6(b). Minutiae Extraction phase.

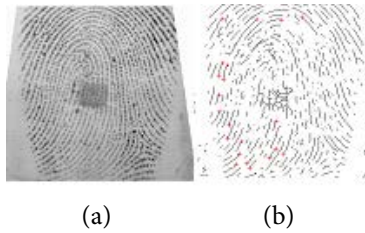


Figure 7. (a). Enhanced Image using Gaussian Low Pass Filter, 7(b). Minutiae Extraction phase.

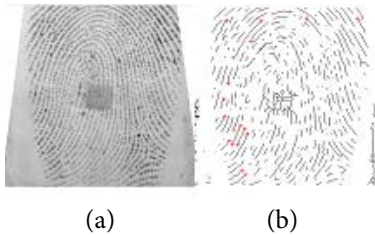


Figure 8. (a). Enhanced Image using Gaussian High Pass Filter, 8(b). Minutiae Extraction phase.

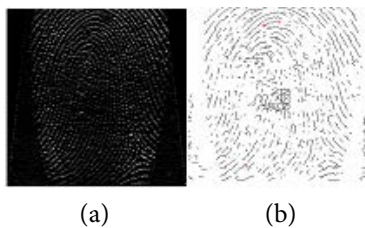


Figure 9. (a). Enhanced Image using Prewitt Filter, 9(b). Minutiae Extraction phase.

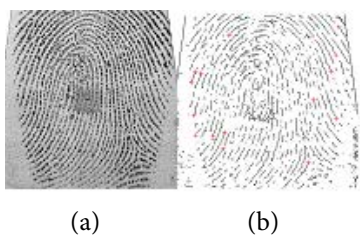


Figure 10. (a). Enhanced Image using Laplacian Filter, 10(b). Minutiae Extraction phase

Prewitt filter is used as the edge detection algorithms. It also enhances the gradient of image intensity at each point. The results of Prewitt filtered image as shown in Figure 9(a) and 9(b) depicts how smoothly or abruptly image changes at that point. Sobel Filter consists of horizontal mask and vertical mask. So, it evaluated more edges as compared to Prewitt as shown in Figure 5 (a) and 5 (b). Gaussian Low Pass Filter has minimized the edge detection content as shown in Figure 7(a) and 7(b) but it enhances the smoothening effect in image. On the other way, Gaussian High Pass Filter concentrates on edge

enhancement content as shown in Figure 8(a) and 8(b). Canny Edge detects unwanted information and preserves useful information present in latent fingerprint as shown in Figure 6(a) and 6(b). For improvement of results obtained from canny edge, Gaussian filter is used to smooth the image so as to avoid the noise effects on edge detector. Laplacian Filter highlights the regions where the intensity keeps on changing rapidly as shown in Figure 10(a) and 10(b).

Finally matching is performed with the changed value of minutiae extracted as shown in Figure 5(a), 5(b) to Figure 10(a), 10(b). The comparison of the results due to different used filters is evaluated in performance evaluation section.

B. Analysis with NIST SD-27 Dataset

For the NIST SD-27 dataset, process of enhancement and minutiae extraction is similarly repeated for the consideration of image, enhancement and minutiae extraction. The input image, manual marking of distorted phase and recovery phase using hybrid PDE & EI is shown in Figure 11(a), 11(b), 11(c).

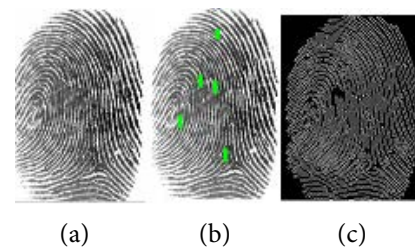


Figure 11. (a). NIST SD-27 dataset Input Image, 11(b). Manual marking of distorted regions, 11(c). Recovered image using hybrid PDE and EI approach.

Further, the recovered image is enhanced using Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, Gaussian High Pass Filter. The enhanced image and minutiae extraction features for different filters is shown in Figure 12 (a), 12(b) to Figure 17 (a), 17 (b).

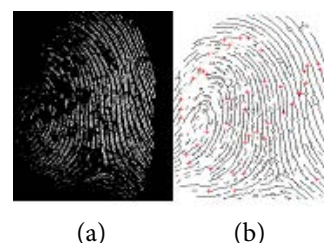


Figure 12. (a). Enhanced Image using Sobel Filter, 12(b). Minutiae Extraction phase.

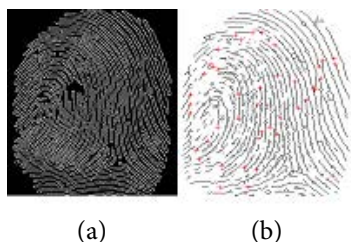


Figure 13. (a). Enhanced Image using Canny Edge Filter, 13(b). Minutiae Extraction phase.



Figure 14. (a). Enhanced Image using Gaussian Low Pass Filter, 14(b). Minutiae Extraction phase.



Figure 15. (a). Enhanced Image using Gaussian High Pass Filter, 15(b). Minutiae Extraction phase.

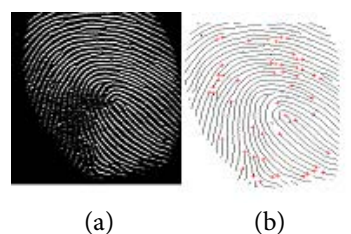


Figure 16. (a). Enhanced Image using Prewitt Filter, 16(b). Minutiae Extraction phase.

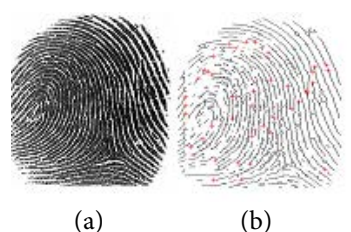


Figure 17. (a). Enhanced Image using Laplacian Filter, 17(b). Minutiae Extraction phase.

Further, Matching is performed for the minutiae extraction image. The overall results for the different filters

for the images of both the NIST SD-27 and IIIT D latent fingerprint datasets is evaluated using the parameters of FAR and GAR.

C. Evaluation Parameters

For the evaluation of proposed concept, we have considered the parameters of False Acceptance Rate (FAR) and Genuine Acceptance Rate (GAR). The basic formulation of these terms is as follows:

- False Acceptance Rate (FAR): FAR is the measure that evaluates the proportion that system incorrectly accepts the unauthorized entity. This can be calculated by the ratio of number of false acceptance made by the system to the total number of attempts. This is shown in equation 1.4:

$$FAR = \frac{\text{Number of Incorrect Accepted Attempts}}{\text{Total number of Attempts}} \quad (1.4)$$

- Genuine Acceptance Rate (GAR): GAR can be defined as the percentage of genuine user accepted by the system. This can be calculated as shown in equation (1.5):

$$GAR = 1 - \text{Number of Genuine users rejected} \quad (1.5)$$

The overall results of both the (NIST SD-27 and IIIT D latent fingerprint) datasets are evaluated in terms of FAR and GAR. For the different filters, values of FAR & GAR varies as the number of ridges, edges, curves, intensity and minutiae information is different extracted. The variation of FAR value as per the different filters depicts variation in the results. For considered datasets, GAR and FAR varies for Sobel filter as shown in Figure 18.

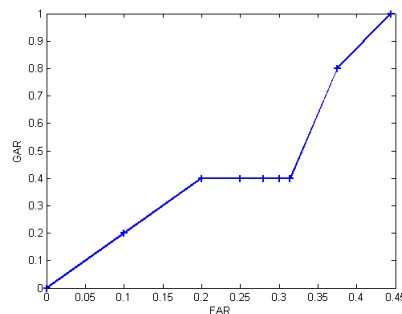


Figure 18. Variation of FAR & GAR value using Sobel filter.

For considered datasets, GAR and FAR varies for Canny Edge filter as shown in Figure 19.

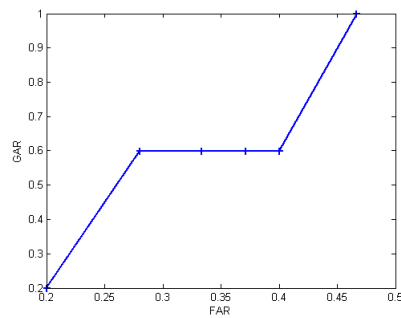


Figure 19. Variation of FAR & GAR value using Canny filter.

For considered datasets, GAR and FAR varies for Gaussian Low Pass filter as shown in Figure 20.

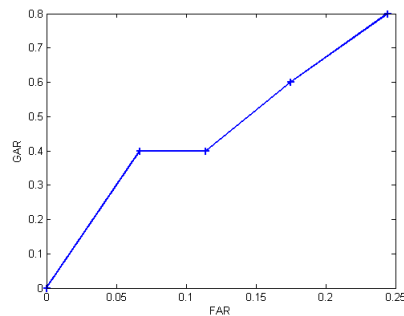


Figure 20. Variation of FAR & GAR value using Gaussian Low Pass filter.

For considered datasets, GAR and FAR varies for Gaussian High Pass filter as shown in Figure 21.

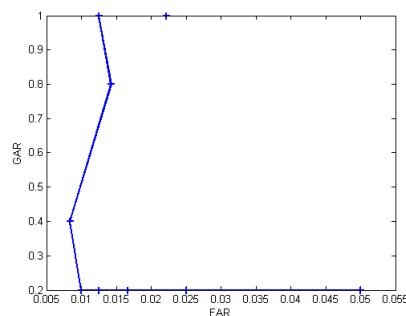


Figure 21. Variation of FAR & GAR value using Gaussian High Pass Filter.

For considered datasets, GAR and FAR varies for Prewitt filter as shown in Figure 22.

For considered datasets, GAR and FAR varies for Laplacian filter as shown in Figure 23.

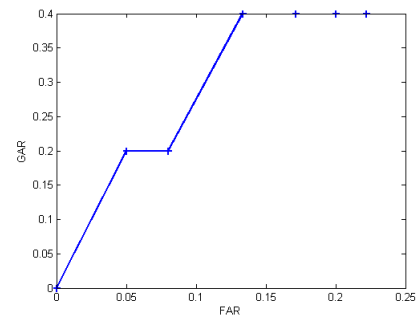


Figure 22. Variation of FAR & GAR value using Prewitt filter.

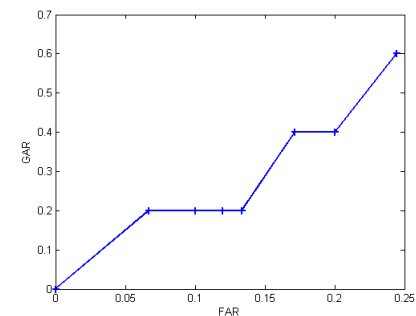


Figure 23. Variation of FAR & GAR value using Laplacian filter.

From Figure 18 to Figure 23, we can say that values of enhancement process varies with different filters of Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, Gaussian High Pass Filter. As each filter enhance different feature of image. So, value of GAR with respect to FAR varies differently.

Further, minutiae extraction phase also shown different value. For this, an average value of minutiae extraction with respect to FAR and Minutiae extraction with respect to GAR value is shown in Figure 24 and Figure 25 respectively.

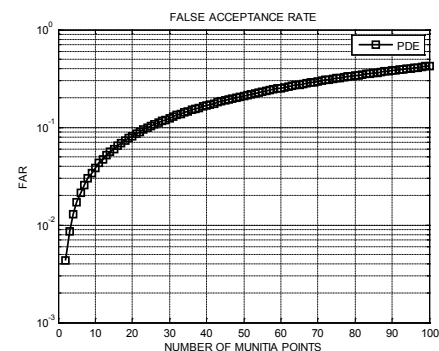


Figure 24. Average FAR value with respect to Minutiae point values.

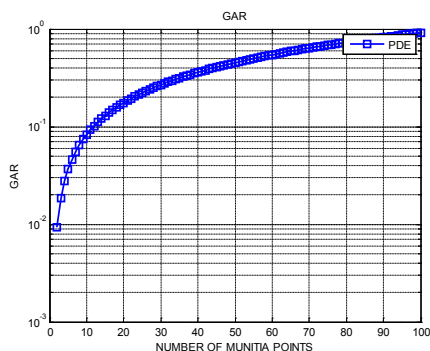


Figure 25. Average GAR value with respect to Minutiae point values.

As per the variation of the GAR values, FAR values vary for different filters and different phase of minutiae extraction as shown in Figure 18 to Figure 25.

Further, to check the acceptance of false identities using the proposed algorithm, GAR value is considered as an optimum fixed value of 40%. At 40% GAR, all the filters are evaluated for FAR values. The calculated percentage of the FAR value using different filters is shown in Table 2.

Table 2. Evaluated FAR value at 40% GAR value

Filters	At 40% GAR, Evaluated FAR value for different filters
Sobel Filter	20%-30%
Gaussian Low Pass Filter	5%
Gaussian High Pass Filter	15%-25%
Prewitt Filter	25%
Canny Edge Filter	1%
Laplacian Filter	18%

To depict the variation in FAR value for 40% GAR, the graphical representation is made as shown in Figure 26.

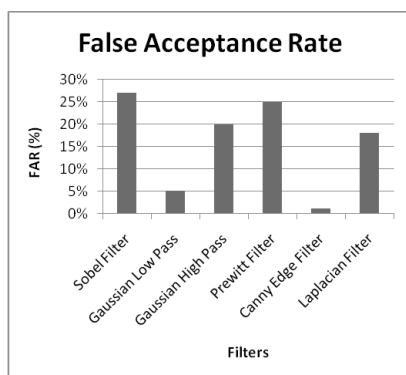


Figure 26. Variation in FAR value for the fixed 40% GAR value.

Lower the value of False Acceptance Rate, more optimized filter to enhance the image as it lesser accepts the false identities. So, Canny Edge filter shows efficient results as compare to other filters.

From the evaluated results, it can be seen that different filters change the matching process and minutiae extraction process. The hybrid approach to recover the broken ridges is important as distorted ridges can't be matched with original fingerprint repository.

7. Conclusion

Latent fingerprint identification is one of well-adapted approaches to catch the criminals by capturing the accidentally left latent fingerprints at crime scene. However, the captured latent fingerprints cannot be recognized due to presence of huge image noise value and distorted ridges of finger impressions. To recognize the fingerprints, it is necessary to recover the broken edges and ridges of finger impressions. Also, need to enhance the fingerprint quality to reduce noise level. In this research work, hybrid approach of PDE and EI is used for the reconstruction of distorted fingerprints. Further image is enhanced using the Canny Edge Detection Filter, Prewitt filter, Laplacian Filter, Sobel Filter, Gaussian Low Pass Filter, and Gaussian High Pass Filter. Performance is evaluated based on the GAR and FAR parameters.

From the evaluated results we can say that values of different filters shows different FAR and GAR rate. In addition, the GAR and FAR values are evaluated with respect to Minutiae extraction process. From the evaluated results, canny edge filter shows efficient compared to other filters. Overall, the proposed approach optimizes the solution to identify the best possible match for latent fingerprints.

8. References

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