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Latent Fingerprint Enhancement via Time Variance Gabor and Sparse Representation

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Abstract: Latent fingerprint images are usually of poor quality with unclear ridge structure. Latent fingerprint identification plays an important role for identifying criminals in law enforcement agencies and resolving various overlapping patterns of fingerprints. Although significant advances and research have been achieved on developing automated fingerprint identification system, it is still challenging to achieve reliable feature extraction and identification for latent fingerprints due to the poor image quality and unclear ridge structure. Earlier to feature extraction, fingerprint enhancement is necessary to minimize various noises and improve the clarity of ridge structures in latent fingerprints. First, the total variation model is used to decompose the latent fingerprint into cartoon and texture components. The cartoon component with most of the non-fingerprint patterns is removed which is known as the structured noise, whereas the texture component consisting of the weak latent fingerprint is enhanced in the next step. Second, we propose a multi scale patch-based sparse representation method for the enhancement of the texture component. Dictionaries are constructed with a set of Gabor elementary functions to capture the characteristics, features and properties of fingerprint ridge structure, and Multi scale patch-based sparse representation is iteratively applied to reconstruct high-quality fingerprint image. The proposed algorithm cannot only remove the overlapping structured noises, but also restore and enhance the corrupted ridge structures. In addition, we present an automatic method to segment the foreground of latent image with the sparse coefficients. On NIST SD27 latent fingerprint database is used to show the effectiveness of the proposed algorithm and its superiority over existing algorithms.

Keywords: Latent fingerprint enhancement, Sparse representation, multi scale patch, gabor filter, structured noise.

I. INTRODUCTION

Latent fingerprint consists of fingerprint images with structured noise. Structured noise is nothing but the object hues, sharp edges, piecewise smooth components, some hand written word or signatures etc. Existing system of fingerprint identification was working on the two types of fingerprint images that are the plain and rolled fingerprint images. In case of latent fingerprint images manual markup system was used. But the manual mark up of latent fingerprints by different examiners reached to the different conclusions for the same image [1]. This confusing situation arises due to the unclear ridge structure of latent fingerprint images.

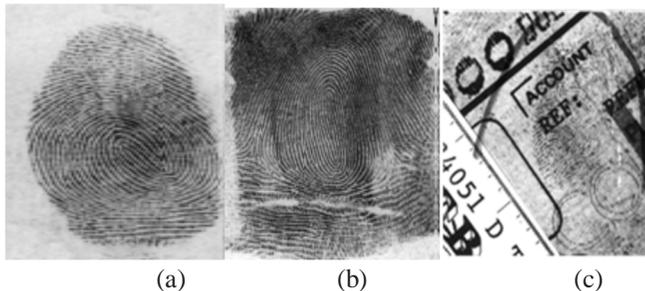


Fig. 1 Types of Fingerprints (a. Plain Fingerprint b. Rolled Fingerprint c. Latent Fingerprint)

Already latent fingerprints are captured from the objects on which concerned person left it accidentally. It may be whole fingerprint, it may be small patch of the fingerprint as it is not given purposefully it has the lot of noises which should be removed first and then enhancing the fingerprint. Automated fingerprint identification system worked well for plain as well as rolled fingerprints but it was challenging for the latent fingerprints [2].

To put latent fingerprints on the flow for research this paper had proposed an algorithm which results in to the denoised enhanced fingerprint image. Fingerprint comparison, fingerprint matching etc topics are applied for rolled and plain fingerprints but the third type latent was kept aside due to it's unclear ridge structure. Therefore for the ease of comparison and matching first step is important that is noise removal and enhancement which we have tried to achieve [3].

The theme is to enhance the poor quality i.e latent images of fingerprints for the ease of their study and successively to identify the criminals. We already have the system for to identify and match the rolled and plain fingerprints, but latent fingerprints are manually matched which is time consuming as well as may create the conflict when two different peoples report.

Latent fingerprints had been using as an important evidence to identify criminals in law enforcement agencies from more than a century. Before introduction of Automated Fingerprint Identification System (AFIS) latent fingerprints were manually matched with the plain and rolled fingerprints samples for to find the suspect. The emergence of AFIS significantly improved the speed of fingerprint matching and of identification. Which was helpful for to identify latent fingerprint match from large database feasible. Over thirty years of development large no of advances had been made on developing AFIS for full print to full print matching. However the compared to the rolled and plain fingerprints, Latent fingerprints are of low image quality, due to the unclear ridge structure, uneven image contrast, and various overlapping patterns such as lines, printed letters, hand writings or even other fingerprints. Due to this low image quality automatic feature extraction is still undesirable to find out the features such as minutia and singular points in latent fingerprints. Therefore latent fingerprints need to manually marked by the latent examiners. However manual mark up of minutia features is not only time consuming but also short of repeatability and compatibility.

First the minutia features in the same fingerprint marked by different examiners may result in different conclusions. Second in current practice, minutia features in latent fingerprints are manually marked while the same for the rolled and plain fingerprints were automatically extracted, which causes a compatibility problem [4], [5].

As the manually markup system is not best solution for the latent fingerprint identification. Before putting latent image to the AFIS it need to undergo with the step of Enhancement which removes the various overlapping patterns, connects broken ridges and separates the overlapping and joined ridges. By considering this situation this project worked on the latent fingerprints identification, enhancement, multi scale representation, and graphical representation followed by dictionary construction.

II. LITERATURE SURVEY

Latent fingerprints are the finger skin impressions found at the crime scene by the criminals left accidentally. Generally those are not directly visible to our eyes. Some physical or chemical methods were used to capture and process such images [1]. Latent fingerprints are used as important proof for to detect the criminals in security systems such as law enforcement agencies. Latent fingerprints are the finger impressions with the poor quality images with unclear ridge structure. There are three main types of fingerprint images such as plain fingerprints, rolled fingerprints and latent fingerprints. The first two plain and rolled fingerprints are having automated systems for their respective processing but latent fingerprints are not having automated system due to their low quality. Latent images were processing manually by the latent examiners. Fingerprints and iris are unique identification of every person base on which each person can be identified uniquely even if these are twins. Therefore fingerprints are being used as an important proof for to identify the criminals in law enforcement system. Fingerprint or the finger skin impression left at the crime scene by the criminal is an important and strong proof for to detect the criminal. There are so many physical or chemical techniques used to capture the skin impressions, because these are not easily visible to our eyes [6]. Before invention of Automated Fingerprint Identification System (AFIS) latent fingerprints were manually matched with the plain and rolled fingerprints samples for to find the suspect among them. The addition of AFIS significantly improved and fasten the speed of fingerprint matching and of identification. Which was helpful for to identify and detect latent fingerprint match from large database feasible. Over thirty years of development large no of advances had been made on developing AFIS for full print to full print matching. However the compared to the rolled and plain fingerprints, Latent fingerprints are of low image quality, due to the unclear ridge structure, uneven image contrast, and various overlapping patterns such as lines, printed letters, hand writings or even other fingerprints. Due to this low image quality automatic feature extraction is still undesirable to find out the features such as minutia and singular points in latent fingerprints. Due to this latent fingerprints were needed to manually marked by the latent examiners. However manual mark up of minutia features is time consuming as well as also short of repeatability and compatibility.

First the minutia features in the same fingerprint marked by different examiners may result in different conclusions. Second in current practice, minutia features in latent fingerprints are manually marked while the same for the rolled and plain fingerprints were automatically extracted, which causes a compatibility problem [7], [8]. As the manually markup system is not best solution for the latent fingerprint identification. Before putting latent image to the AFIS it need to undergo with the step of Enhancement. This

enhancement step removes the various overlapping patterns, connects broken ridges and separates the overlapping as well as joined ridges. The incomplete ridge and valley flows of fingerprints combined forms a sinusoidal shaped plane wave with well-defined frequency and orientation in a local neighborhood. There were no of methods were designed for to take the advantage of this information and to enhance the poor quality fingerprints.

A. Gabor Filter.

Gabor Filter is defined with a sinusoidal plane wave structure tapered by a Gaussian methodology. Gaussian can capture the periodic, yet non stationary nature of fingerprint ridge structure. Gabor filtering is rarely used for fingerprint enhancement. In this method on the basis of local neighborhood, local ridge orientation and frequency are firstly estimated for each pixel based on local neighborhood. Then Gabor filter is tuned with local orientation and frequency and applied on the image pixel to remove the undesired unnecessary noise and improve the clarity of ridge structure. The basic requirement of this method is estimation of local ridge orientation and frequency and which is challenging for poor quality fingerprint [9].

B. Short Time Fourier Transform (STFT)

It is another technique used for contextual filtering in Fourier domain for fingerprint enhancement. The Classical traditional 1D (One Dimensional) time frequency analysis is renewed to 2D (2 Dimensional) fingerprint images for short time or short space frequency analysis. The probable estimate of foreground region mask, ridge orientation and frequency are simultaneously computed from STFT analysis. The full length information of context including local orientation, angular coherence is utilized for fingerprint enhancement. The above given enhancement algorithms were usually developed for the rolled and the plain fingerprints. There are following types of image enhancement. Image enhancement aims to improve the visual appearance of an image, in other words we can say that image enhancement is technique to provide a better transform representation for future automated image processing [6]. There are different types of image enhancement. Image enhancement techniques in spatial domain can be broadly categorized in to two types i. e. Spatial based domain image enhancement and frequency based domain image enhancement. Spatial based domain image enhancement consists of operation on pixels [10], [11], [12]. The pixel values are manipulated to gain the desired enhancement. The main advantage of these techniques is that they are easy, conceptually simple for understanding. Another advantage is that in case of real time implementations their complexity is very low. Frequency based domain image enhancement consist of analysis of mathematical functions as well as signals with respect to frequency and it operates directly on transform coefficients of the image. Some examples of frequency based techniques are Fourier transform. The basic limitation is that it cannot enhance all the parts of an image simultaneously. A durable method was proposed for estimation of orientation and for to improve the performance of latent fingerprint enhancement by using gabor filter. This method made the use of STFT method to obtain multiple orientation elements in each and every image blocks, and set of hypothesized orientation fields were generated with hypothesize and test paradigm based on the randomized RANSAC. Its requirement is manual markup of singular points and region of interest (ROI) for enhancement. In recent years a robust method to estimate orientation field using the prior knowledge of fingerprint ridge structure, which is represented by a dictionary of reference orientation patches as well as compatibility constraint between neighboring orientation patches. Energy of loopy belief propagation get minimized by the fingerprint orientation field computation by a combination of candidates. To achieve improvement for enhancement of latent fingerprints, gabor filtering was applied with the combination of robust orientation estimation. Even if all above methods set the fixed ridge frequency to tune the gabor filters for enhancement. In real practice it is not always constant in fingerprint image, which makes limitation for the enhancement performance of gabor filtering [13].

C. Total Variation Model

A total Variation (TV) image model minimizes the total variation of the image which can be studied for image decomposition. Generally, the TV model decomposes image into two sub components: Texture and Cartoon components.

Texture components can be identified as repeated oscillatory and meaningful structure of small fingerprint patches patterns. Noise components can be identified as uncorrelated random patterns. The remaining of an image that is the cartoon component, includes the object hues, sharp edges, and piecewise smooth components. TV model was proposed preferably for to remove noises structured or unstructured for latent fingerprint segmentation [14].

D. Adaptive Directional Total Variation Model

Further advancement is an adaptive directional total variation (ADTV) model by integrating the local orientation and scale for fingerprint segmentation and enhancement. These TV based methods divides latent image into texture and cartoon components. The

texture components mainly include oscillatory fingerprint ridge patterns whereas the cartoon components contain the left unwanted contents, such as structured noises. By removing structured noises latent fingerprint segmentation and enhancement procedures are performed on the texture components. Even if it is not too much easy to accurately and reliably estimating the local parameters such as ridge orientation and scale of ADTV model for latent images of poor quality. With the addition to these corrupted noisy regions are not restored and the extracted fingerprint pattern is usually very weak and unclear, which will bringing the limitation on the performance of latent fingerprint identification. The dictionary based approach was designed to enable the reliable and accurate estimation of ridge orientation and frequency fields and facilitate the process of automatic segmentation and enhancement of related latent fingerprints. By applying TV model piecewise smooth and structured noises can be removed up to considerable extent [15].

E. Sparse Representation

Here the patch size is an important parameter for fingerprint reconstruction. Large patch can suppress the noise better whereas the small patch can preserve the details of ridge structure. To achieve both noise robustness and detail preserving we propose a multi scale representation [16].

III. SYSTEM DEVELOPMENT

The main objective of the latent fingerprint enhancement is to remove the irrelevant contents while enhancing the clarity of fingerprint ridge and valley structure, which is generally considered as the image denoising and the restoration problem. To address such problems we have proposed a latent fingerprint enhancement via multi scale patch based sparse representation algorithm system which includes the image decomposition and restoration followed by reconstruction.

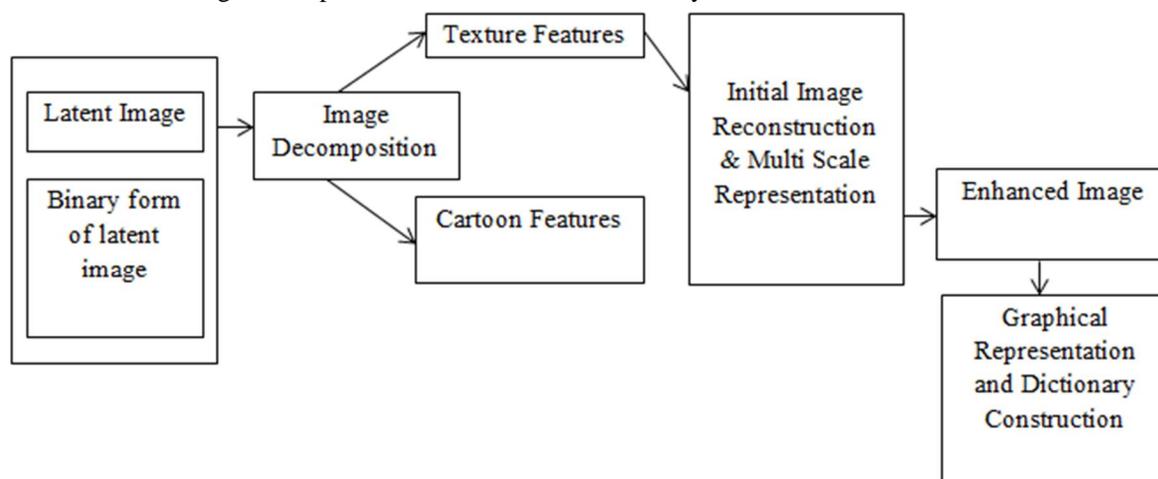


Fig 2. Flowchart of Latent Fingerprint Enhancement System

First to decompose the latent image into cartoon and texture components the TV model is applied. The cartoon components such as the structured noises and the irrelevant contents are discarded. Next step is image reconstruction by using the multi scale sparse representation from the texture components. Firstly small patch size is preferred because the small patch size can preserve the ridge details properly. To restore the corrupted ridge structure due to the noise, multi scale patch based sparse representation method is preferred to repeatedly reconstruct the high quality fingerprint image with gradually changing the patch size. The next step is Segmentation for to generate the Region of Interest (ROI) for further enhancement process. Enhancement is followed by the dictionary construction.

A. Latent Fingerprint Decomposition with the TV Model

Consider the given function y , the decomposition can be formulated as $y = u + v$ where u represents the piecewise smooth component and the v is oscillatory texture noise component. Here if considered generally, image decomposition can be obtained by minimizing the total variation.

$$\text{Min}\{TV(u) \mid \|u - y\|_B \leq \varepsilon\} \quad (1)$$

Here $TV(u)$ gives the total variation of u and $\|\cdot\|$ is a norm. $TV(u)$ is minimized to regularize the image u without smoothing the edges of y into u . The term $\|u - y\|_B$ Known as the fidelity term as it forces u to be close to y . In latent image, fingerprint pattern is made up of parallel ridge and valley flows. This is matching with oscillatory characteristics of texture components of v . Characters, handwritings, lines, arches etc. non fingerprint contents usually have the smooth inner surface and crisp edges, which share the similar characteristics with the cartoon components of u . In this work TV model is used for to decompose the latent image into the texture and the cartoon components. After the cartoon and texture decomposition, not only the structured noises but also the effect of the varying illumination had been significantly get reduced in the extracted texture components, which generates the several problems as given follows:

- 1) Although the structured noises are significantly reduced in the texture component the fingerprint pattern with oscillatory behaviors are also reduced to some extent.
- 2) The fingerprint regions which are destroyed due to structured noises are not restored and the fingerprint patterns with the oscillatory broken ridges may get result into false and missing extraction of the various features.
- 3) Texture components are found with some small and random structured noises.
- 4) Due to the smooth boundaries and use of finite differentiating a small amount of the boundary signals near to the non-smooth edges will appear in the extracted pattern.

Due to these problems, the extracted fingerprint patterns are too weak to be applied for feature extraction as well as matching. Multi scale patch based sparse representation method will be presented for the enhancement of the extracted fingerprint in the given sections.

B. Latent Fingerprint Enhancement by Multi Scale Patch Based Sparse Representation.

Mathematically we can say that a real valued signal $y \in R^N$ can be represented by a linear combination of a set of the N dimensional basis atoms:

$$Y = \sum_i \phi_i \Psi_i + e = \Phi \alpha + e \quad (2)$$

Here $\Phi = \{\Psi_1, \Psi_2, \dots, \Psi_M\} \in R^{N \times M}$ Dictionary inclusive of a set of representative basis atoms;

$\alpha = \{\alpha_1, \alpha_2, \dots, \alpha_M\}$ denotes the basis coefficient vectors;

e denotes additive noise superimposed on the signal.

In real situation dictionary Φ and an image patch $y \in R^N$ convex relaxation is adopted to change the l_0 norm regularized minimization into a convex optimization with the l_1 norm regularization:

$$\min \|\alpha\|_1 \quad \|y - \Phi \alpha\|_2^2 < \epsilon \quad (3)$$

the penalty quantifying sparsity and $\epsilon > 0$ is a tuning parameter for to control the fidelity of the model approximation to y . There are number of approaches proposed to solve this least squares optimizations with l_0 norm regularization.

- 1) Gabor Dictionary Construction: The first step of latent fingerprint enhancement consists of usage of sparse representation to construct the redundant dictionary. To gain good representation dictionary should characterize every kind of image structures and details. 2D sinusoidal shaped wave with well-defined orientation and frequency are formed by local fingerprint patches. Gabor functions are having both frequency and orientation selective properties. They have optimal joint resolution in both spatial as well as frequency domains. They capture the periodic and non-stationary characteristics of the fingerprint pattern. Also they form a very intuitive representation of the fingerprint images. Therefore it is appropriate to use gabor functions to model the local patch of latent fingerprint images. The 2D Gabor functions are having general form as given below.

$$h(x, y, \theta, f) = \exp\{-1/2 [\frac{x\theta^2}{\delta x^2} + \frac{y\theta^2}{\delta y^2}]\} \cos(2\pi f x \theta + \varphi_0) \quad (4)$$

$$x\theta = x \cos \theta + y \sin \theta \quad (5)$$

$$y\theta = -x \sin \theta + y \cos \theta \quad (6)$$

here θ gives orientation of the normal with the parallel stripes of the Gabor Function f is Frequency of sinusoidal plane wave δx and δy are the space constants of the Gaussian envelope along x and y axes respectively. φ_0 is the phase offset of the gabor function. The dictionary is constructed to capture the various characteristics of local ridge patterns with a set of basis atoms generated by variable parameters of gabor functions in to valid range. We have set $\delta x = \delta y$ equal to the patch size. Frequency changes from 5 to 21. θ varies from 0 to $15\pi/16$ at a step of $\pi/16$ to have 16 values. φ_0 varies from 0 to $\pi/6$ to have 6 values. Then each Gabor atom is preprocessed to have zero mean and l_2 norm of 1. Finally around 864 atoms are generated to construct the dictionary for the sparse fingerprint representation.

C. Multi Scale Iterative Sparse Representation.

As described above ϕ dictionary for each image patch a sparse coefficient vector can be obtained with the help of solution of optimization problem in equation 3 then the local fingerprint patch is reconstructed by $y = \phi\alpha$ From left to right and from top to bottom the patches are processed in raster order for the reconstruction of the whole fingerprint. Here the patch size is playing most important role to determine the quality of reconstructed fingerprint image. Large patch can suppress the noise better But the problem is that it smooth the ridge details I e ridge ending and the bifurcation values which are important and fine level features of recognition process. Opposite to it a small patch can preserve the ridge details but it is sensitive to the noise. An important problem in fingerprint image reconstruction is that how to smooth the noise while we are preserving the minute details.

To solve this problem we propose to perform the sparse representation through the multi scale descriptions of the images. Successively equation 3 is modified to constrain the reconstruction $\phi\alpha$ of the patch y to closely agree with both small as well as large patches:

$$\min\|\alpha\|_1 \quad \|\|y_s - \phi_s \alpha\|_2^2 < \epsilon 1; \quad \|\|y_l - \phi_l \alpha\|_2^2 < \epsilon 2 \quad (7)$$

Here y_s and y_l Are the small and large patches to be approximated. ϕ_s and ϕ_l are the dictionaries to respective small and large patches These are constructed by the same set of Gabor functions with only difference in the space constants of the Gaussian envelope. Their respective dictionary atoms are generated with the same orientation and frequency parameters to offer the multi scale patch based sparse representation and reconstruction.

$$\alpha^{\wedge} = \arg \min \|\|y_s - \phi_s \alpha\| + \gamma\|\|y_l - \phi_l \alpha\| + \lambda\|\alpha\|_1 \quad (8)$$

Here γ and λ are the linear regression The parameter λ is set to 0.5 in the experiment for to balance the sparsity and theapproximation fidelity. Here the given optimal solutionto equation 8 as

$$\alpha^{\wedge} = \arg \min \|\|y_s - \phi_s \alpha\| + \lambda\|\alpha\|_1 \quad (9)$$

the image patch can be reconstructed with the dictionary of the small scale as the total fingerprint can be processed as in raster scan order form the left to right and top to bottom.

D. Fingerprint Segmentation

Instead of using the manual mark up process of ROI of latent image we have performing the automatic segmentation of useful ridge like fingerprint region based on the initial reconstructed image via sparse representation. It consist of two steps as in Equation (9) measure the weights of the basis atoms in representation of patch p , the sum of the absolute coefficients if it is small and p is non-fingerprint patch. If it is less than T the patch is segmented as the background. Second step is computation of the orientation coherence with an Equation (10) for to measure the quality of the reconstructed fingerprint.

E. Dictionary Construction

As the latent fingerprint is converted into the simple fingerprint or the plain fingerprint each image is stored in the form of graphical representation for the ease of future use and feature extraction as well as matching .

F. Algorithm1 Latent Fingerprint Enhancement via Wiener Filter

1) Input: Y :The latent fingerprint

W_s : Size of Small Patch

$G(u,v)$: Wiener Filter

2) First Step: Initial Fingerprint reconstruction with small patch.

Go through the image patch y of Y from the upper left corner with 8 pixel forward step, and then repeat the following steps:

Normalize the image patch y to have unit l_2 norm.

Solve the minimization problem to obtain the sparse coefficients α

Reconstruct the image Patch as $y_{new} = \phi_s \cdot \alpha$

3) Second Step: Apply Wiener filter on

$y_{new} = \phi_s \cdot \alpha$

as

$Y_{new} = G(u,v) * Y(x,y)$

4) Repeat step 3 until $Y(x,y) = S_p$

Output: The enhanced Fingerprint Y_{new} .

Algorithm 2 Fingerprint Enhancement by Multi Scale Patch Based Sparse Representation:

a) *Input: Y* :The latent fingerprint

Ws: Size of Small Patch

ϕ_s : Gabor dictionary for small patch selected

b) *First Step*: Initial Fingerprint reconstruction with small patch.

Go through the image patch y of Y from the upper left corner with 8 pixel forward step, and then repeat the following steps:

Normalize the image patch y to have unit l2 norm.

Solve the minimization problem to obtain the sparse coefficients α

Reconstruct the image Patch as $y_{new} = \phi_s \cdot \alpha$

Second Step:

Iterative reconstruction of poor quality fingerprint regions through multi scale patches. Given the initial result perform the following steps in each iteration:

- i) Set the large patch size $w_l > w_s$ and construct the corresponding gabor dictionary ϕ_l
 - ii) Compute the image quality of initial image result with equation and separate the poor quality image of latent fingerprint as S_p .
 - iii) For each image patch S_p in region repeat following steps:
 Normalize the small image patch y_s to and the large image patch y_l to have unit l2 norm
 Solve minimization problem with ϕ_s, ϕ_l, Y_s, Y_l to obtain the sparse coefficients α
 Reconstruct the image patch as $y_{new} = \phi_s \cdot \alpha$
 - iv) Output y as Y_{new} and increase the patch size $w_l = w_l + 4$.
 - v) Go to step 1 until $S_p = \emptyset$ or arriving the maximum iteration
- Output: The enhanced Fingerprint Y_{new} .

IV. PERFORMANCE ANALYSIS

To verify the performance of proposed method, Latent fingerprint images are collected as training data from the standard data set NIST Sd27. We perform latent fingerprint enhancement on each image and got the large difference in output entropies between two filters. As an Entropy gets lowered than the input image it is noticed that the noise in an image is minimized. Here is an example showing original Input Image, Output image using Wiener filter and output image using Gabor filter respectively.



Fig 3 a) Original input image b) Output image of Wiener filter c) Output image of Gabor filter

Graph given below show the difference between entropies when applied wiener filter and the gabor filter with TV model respectively.

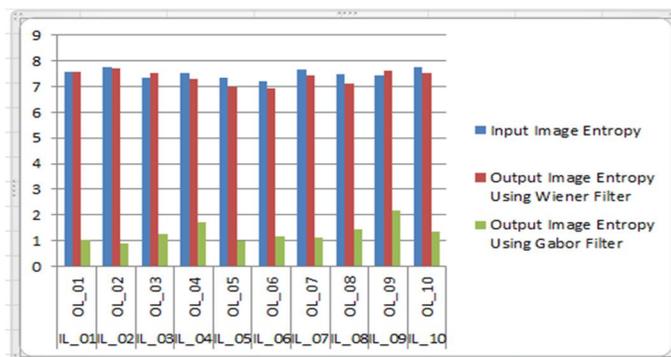


Fig 4 Working of Wiener filter vs Gabor filter

For to show the experimental accuracy we divide the output entropy values(En) in three categories as $En < 0.9$ then rank as Poor. If $En > 0.9$ & < 1.2 then rank as Good and if $En >> 1.2$ then rank as Better.

This ranking shows usefulness of the image is while studying for fingerprint matching, feature extraction etc. Although the noise is completely removed but if the very small patch is get extracted then it is ranked as poor, when it is near to considerable extent then it is ranked as Good and if it is more than half fingerprint then it is marked as Better.

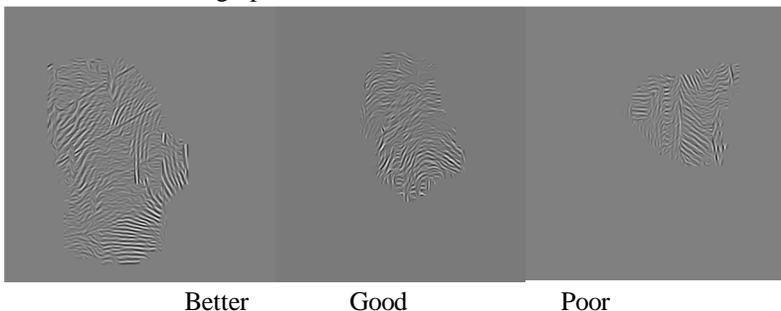


Fig 5 Ranking of Output Images

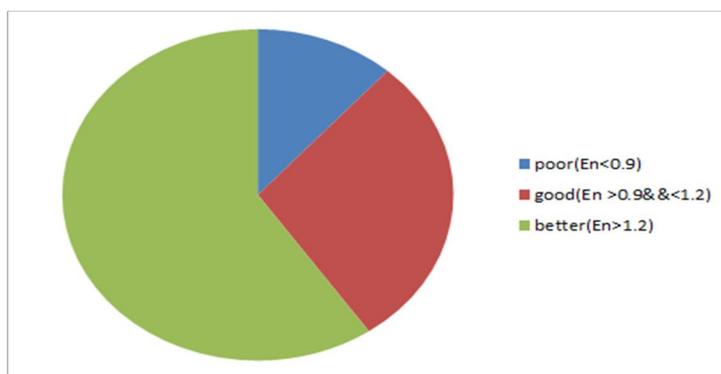


Fig. 6 Ranking of output using Gabor filter

When two algorithms are compared we get the following graph showing that the noise is reduced more by the gabor filter than that of Wiener filter

Sr. No.	Input Image Name	Output Image Name	Input Image Entropy	Output Image Entropy Using Wiener Filte	Output Image Entropy Using Gabor Filter	Rank
16	IL_16	OL_16	7.7794	7.2555	0.3788	Poor
27	IL_27	OL_27	7.7583	7.6187	0.7195	Poor
15	IL_15	OL_15	7.303	7.3471	0.8535	Poor
18	IL_18	OL_18	6.5826	7.4437	0.865	Poor
17	IL_17	OL_17	7.3567	7.3444	0.8689	Poor
2	IL_02	OL_02	7.7361	7.7273	0.8847	Poor
32	IL_32	OL_32	7.3405	7.0038	0.9231	Good
48	IL_48	OL_48	7.4282	6.8243	0.9297	Good
20	IL_20	OL_20	7.5462	7.2488	0.9342	Good
13	IL_13	OL_13	7.4857	7.6235	0.9441	Good
14	IL_14	OL_14	7.6607	7.3813	0.9441	Good
33	IL_33	OL_33	7.4339	7.2327	0.9553	Good
38	IL_38	OL_38	7.5966	7.1374	0.9798	Good
5	IL_05	OL_05	7.365	6.978	0.981	Good
12	IL_12	OL_12	6.6539	7.6177	0.9862	Good
22	IL_22	OL_22	7.0112	6.9288	1.017	Good
28	IL_28	OL_28	7.421	6.9955	1.0402	Good
1	IL_01	OL_01	7.5772	7.5644	1.0525	Good
7	IL_07	OL_07	7.6439	7.4523	1.1006	Good
43	IL_43	OL_43	7.6665	7.5992	1.107	Good
34	IL_34	OL_34	6.974	7.0048	1.1685	Good
6	IL_06	OL_06	7.2261	6.9348	1.186	Good
40	IL_40	OL_40	7.3437	7.5251	1.1913	Good
44	IL_44	OL_44	7.4365	7.3399	1.2008	Better
11	IL_11	OL_11	7.6114	7.633	1.2571	Better

30	IL_30	OL_30	7.6294	7.2807	1.3567	Better
10	IL_10	OL_10	7.7476	7.5209	1.3622	Better
41	IL_41	OL_41	7.7461	7.5189	1.3732	Better
52	IL_52	OL_52	7.1794	6.5254	1.3857	Better
35	IL_35	OL_35	7.3286	6.8027	1.4073	Better
46	IL_46	OL_46	7.5184	7.3249	1.4113	Better
29	IL_29	OL_29	7.4224	6.9976	1.414	Better
8	IL_08	OL_08	7.4727	7.1232	1.4246	Better
39	IL_39	OL_39	6.7013	6.8993	1.5896	Better
26	IL_26	OL_26	7.3696	6.9441	1.6136	Better
49	IL_49	OL_49	7.3749	7.5455	1.6202	Better
47	IL_47	OL_47	7.7549	7.4847	1.6206	Better
25	IL_25	OL_25	7.1532	6.9508	1.672	Better
21	IL_21	OL_21	6.988	7.6176	1.7005	Better
4	IL_04	OL_04	7.5281	7.3029	1.7292	Better
19	IL_19	OL_19	5.9864	7.3039	1.7722	Better
36	IL_36	OL_36	7.4904	7.5453	1.8426	Better
37	IL_37	OL_37	6.2779	6.0958	1.9044	Better
51	IL_51	OL_51	7.1778	7.2274	1.9929	Better
24	IL_24	OL_24	7.4155	7.2222	2.019	Better
31	IL_31	OL_31	7.2577	6.8122	2.0726	Better
9	IL_09	OL_09	7.4341	7.5999	2.1869	Better
23	IL_23	OL_23	7.0157	7.228	2.7229	Better
45	IL_45	OL_45	7.7174	7.3494	2.8203	Better
42	IL_42	OL_42	7.7283	7.2898	3.5225	Better

Fig 7 Table showing ranking of output images on the basis of Entropies of input and output images.

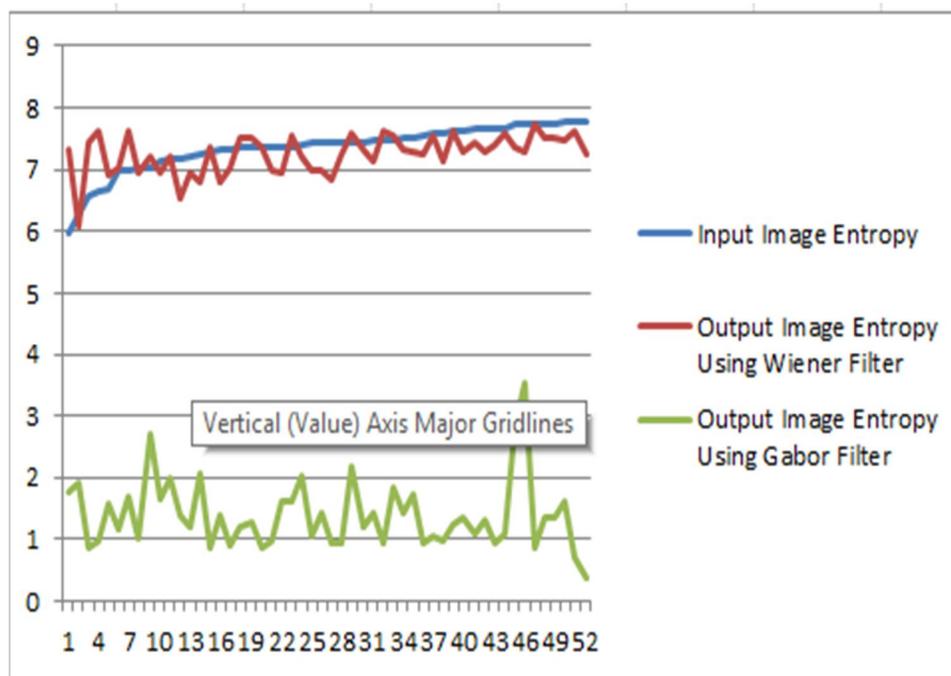


Fig 8 Input Image Entropy vs Wiener filter output vs Gabor filter

V. CONCLUSION

In this paper, we have proposed a latent fingerprint enhancement algorithm, which is useful for combining TV model and the multi scale patch based sparse representation for removing noises and improving the clarity of ridge structure. The proposed method not only can remove various structured noises but also can restore and enhance the corrupted fingerprint ridge structures. Entropies of the Input and the output images shows the large difference which proves the accuracy of an algorithm. To demonstrate Experimental results NIST SD27 database have been presented for the effectiveness and superiority of the proposed algorithm.

REFERENCES

- [1] C. Champod, C. J. Lennard, P. Margot, and M. Stoilovic, *Fingerprints and Other Ridge Skin Impressions*, vol. 102. Boca Raton, FL, USA: CRC Press, 2004, pp. 114–131.
- [2] S. Yoon, J. Feng, and A. K. Jain, “On latent fingerprint enhancement,” *Proc. SPIE*, vol. 7667, p. 766707, Apr. 2010.
- [3] D. R. Ashbaugh, *Quantitative-Qualitative Friction Ridge Analysis: An Introduction to Basic and Advanced Ridgeology*. Boca Raton, FL, USA: CRC Press, 1999.
- [4] A. K. Jain and K. Nandarkumar, “Fingerprint matching,” *IEEE Comput.*, vol. 43, no. 2, pp. 36–44, Feb. 2010.
- [5] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*. New York, NY, USA: Springer-Verlag, 2003.
- [6] R. Cappelli, A. Lumini, D. Maio, and D. Maltoni, “Fingerprint classification by directional image partitioning,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 21, no. 5, pp. 402–421, May 1999.
- [7] X. Jiang, M. Liu, and A. C. Kot, “Fingerprint retrieval for identification,” *IEEE Trans. Inf. Forensics Security*, vol. 1, no. 4, pp. 532–542, Dec. 2006.
- [8] M. Liu, X. Jiang, and A. C. Kot, “Efficient fingerprint search based on database clustering,” *Pattern Recognit.*, vol. 40, no. 6, pp. 1793–1803, Jun. 2007.
- [9] M. Liu and P.-T. Yap, “Invariant representation of orientation fields for fingerprint indexing,” *Pattern Recognit.*, vol. 45, no. 7, pp. 2532–2542, Jul. 2012.
- [10] S. Liu and M. Liu, “Fingerprint orientation modeling by sparse coding,” in *Proc. 5th IAPR Int. Conf. Biometrics (ICB)*, New Delhi, India, Mar./Apr. 2012, pp. 176–181.
- [11] A. K. Jain and J. Feng, “Latent fingerprint matching,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 1, pp. 88–100, Jan. 2011.
- [12] B. T. Ulery, R. A. Hicklin, J. Buscaglia, and M. A. Roberts, “Repeatability and reproducibility of decisions by latent fingerprint examiners,” *PLoS ONE*, vol. 7, no. 3, p. e32800, 2012.
- [13] J. Feng, J. Zhou, and A. K. Jain, “Orientation field estimation for latent fingerprint enhancement,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 4, pp. 925–940, Apr. 2013.
- [14] L. Hong, Y. Wan, and A. Jain, “Fingerprint image enhancement: Algorithm and performance evaluation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 8, pp. 777–789, Aug. 1998.
- [15] R. Cappelli, D. Maio, and D. Maltoni, “Semi-automatic enhancement of very low quality fingerprints,” in *Proc. 6th Int. Symp. Image Signal Process. Anal.*, Salzburg, Austria, Sep. 2009, pp. 678–683.
- [16] S. Chikkerur, A. N. Cartwright, and V. Govindaraju, “Fingerprint image enhancement using STFT analysis,” *Pattern Recognit.*, vol. 40, no. 1, pp. 198–211, 2007.



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