

A Review of Dictionary Based Approaches for Latent Fingerprints

Manvjeet Kaur, Assistant Professor, Punjab Engineering College (Deemed to be University),
Chandigarh, India, manvjeet@pec.ac.in

Ritika Dhaneshwar, M. Tech. Scholar, Punjab Engineering College (Deemed to be University),
Chandigarh, India, ritikadhaneshwar@gmail.com

Abstract - Latent fingerprints are accidental impressions left by friction ridge skin on a surface. Detection of such fingerprints which are not visible to naked eyes can be done using various methods like chemical method, powder method (Fluorescent powder, magnetic powder etc), alternate light sources etc. The print residues that are left at crime scene are generally of very poor quality due to complex background noise, poor ridge quality, overlapping structures, patches and gaps in fingerprints etc. Because of poor fingerprint quality, feature extraction and enhancement is a grave challenge. In order to correct the orientation field and fill the gaps and patches in the input image, a dictionary of good quality reference prints is created. This Dictionary based learning technique helps in reconstruction of latent fingerprint image and its further enhancement. In this paper a review of dictionary based approaches for latent fingerprints is presented.

Keywords — Dictionary based learning, Enhancement, Latent fingerprint, Orientation field, Reference print, Reconstruction.

I. INTRODUCTION

Uniqueness and permanence are the two properties based on which fingerprints are identified. It has been claimed that fingerprints are unique and no two individuals have the exact same fingerprints. The fingerprint of an individual does not change in its lifetime, except in some conditions like permanent scar due to injury. Location of minutiae forms the bases for Fingerprint analysis. Based on location and orientation, fingerprint features are of following three types as shown in Fig1[1]:

Level-1: The features categorized as level-1 are core, delta points, ridge flow configurations like orientation field, arch, whorl and loops are used for classification.

Level-2: Ridge discontinuities also known as ridge endings and bifurcation comes under this category.

Level-3: Pores, line shapes, scars and ridge contours are known as level 3 features.

Latent fingerprints, are invisible patterns that are usually left at crime scenes, accidentally. Fingerprints found at crime scenes are most cardinal and widely used proof in law enforcement and forensic agencies for identifying and convicting criminals. There are various known methods for latent fingerprint reconstruction and enhancement like image inpainting [2], Iterative reconstruction [3], ConvNet based approach [4], dictionary based approach etc. Amongst the various approaches, dictionary based approach is widely used. In this approach a dictionary of good quality reference patches is created which is further used for

reconstruction of image. From the dictionary the best possible match is selected and replaced to fill the gaps in the distorted latent image.

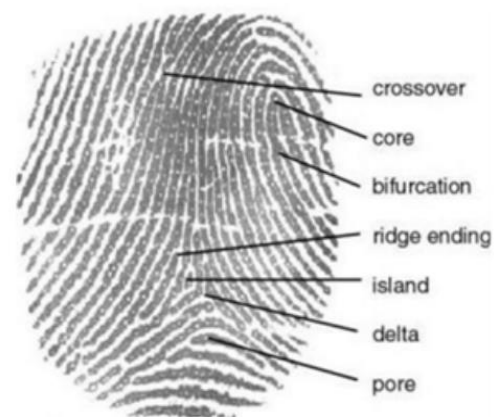


Fig.1: Features in Fingerprint image [1]

II. DICTIONARY BASED APPROACHES

A Dictionary is defined as collection of good quality reference patches known as dictionary elements. These elements are used for reconstruction and enhancement of latent fingerprints. Major advantage of using dictionary based approach is that it utilizes the prior knowledge for reconstruction and enhancement of fingerprints. Fig.2 depicts the basic flow diagram of dictionary based approach.

There are four broad approaches using which a dictionary can be created, which are discussed as follows-

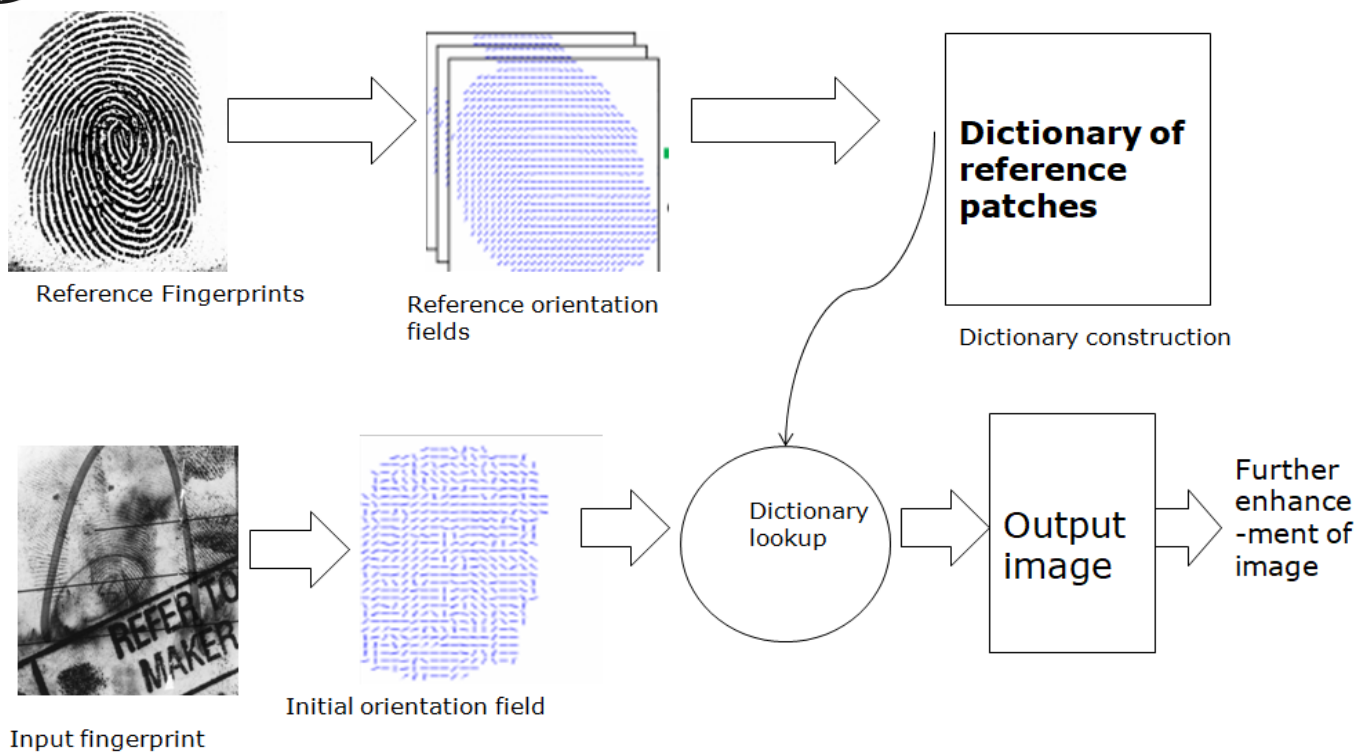


Fig2: The basic flow diagram of dictionary based approach

A. Global dictionary based approach

A global dictionary based approach for latent fingerprint enhancement was proposed in [5]. In this approach a dictionary is constructed which consist of orientation patches of the equal size. An orientation element in this approach is defined as a dominant orientation in a block of size 16*16 pixels. By using a b*b window size they obtained orientation patches for dictionary creation. As the direction of the latent fingerprint is unknown, the orientation patch obtained are rotated by 21 different angles. Greedy algorithm was used to create a collection of reference orientation patches by discarding repetitive patches, in order to create the dictionary. The number of reference orientation fields and the size of the patch are the two criterion based on which count of reference orientation patches in the dictionary depends. The manual marking is still superior to the proposed approach especially on low-quality latent. The major disadvantage of their dictionary is that since ridge information is not taken into account it cannot be successfully used for latent segmentation. The drawback of using a single global dictionary is that false local ridge patterns may appear at certain locations of fingerprints. In order to overcome the shortcomings of this approach localized dictionary based approach was proposed.

B. Localized Dictionary Based Approach

Since ridge orientations in a fingerprint have different characteristics at different locations of fingerprints, an orientation field estimation approach using localized

dictionaries is required wherein distorted orientation patch is replaced by actual orientation patch.

A large longitudinal fingerprint database was used in [6] to learn a dictionary of orientation field using fingerprint alignment. The database contain 15,597 subjects of longitudinal records, with each individual having at least five 10-print records over a minimum time span of 5 years. In order to learn an orientation field dictionary a self-organizing map (SOM) is used. The block size of 16*16 is used for orientation field extraction. When there is time period lag between comparisons of two fingerprints, genuine match scores decreases. So to overcome this problem this approach was proposed.

A new dictionary creation technique was proposed in [7]. In this technique using concept of clustering a localized dictionary in the finger coordinate system is obtained. The size of the patch used is 6*6. The first step is to add all the orientation patch in T_u into D_u . The threshold is selected as 0.8 in order to calculate similarity between patches. Using the above clustering procedure a set of localized dictionaries are obtained [8].

The cardinal difference observed when compared with the approach proposed in [5] is that, instead of using one dictionary, author uses a set of localized dictionaries. The motivation behind using localized dictionaries is driven by the fact that there are different characteristics corresponding to ridge orientations in different regions of fingerprints. Therefore, instead of using one dictionary of orientation patches for the entire fingerprint as in [5], they created a distinct dictionary for each location. Both the non-word

errors and the real word errors are reduced by using localized dictionaries.

The advantage of using localized dictionaries over a global dictionary with respect to lookup are- All the patches which are not found at specified positions are not considered and the number of the patches in a global dictionary is much greater than the local one.

Localized dictionaries are faster to construct because of the following reasons- The time taken by the clustering algorithm is of the order of $O(n^2)$, where n represent the number of samples, and Only orientation patches in the same location are used for construction of local dictionary.

C. Ridge structure based dictionary approach

The dictionary constructed using ridge structure uses a collection of rolled fingerprint patches of high quality. The constructed dictionary is further used recreate the ridges from distorted latent patches.

The dictionary creation method proposed in [9] is as follows. In the first step they recorded the variation of orientation patches using patterns such as whorl, arches and loops. This helped them to extract good quality full template fingerprints. The composition of orientation field are calculated at discrete locations of fingerprint image. Further, each fingerprint is partition into blocks of $16*16$ pixels such that the blocks do not overlap each other. After dividing the fingerprint into blocks, for each block ridge orientation is calculated. The orientation is denoted as $\theta(m, n)$ where m are coordinates in horizontal direction and n represent vertical directions coordinates. In order to get good results dictionary size should be of appropriate size. If the size is small, computation is time efficient but it may not be good enough for effective reconstruction. On the other hand if it is large, the cost for computation is very high.

When compared it with the dictionary based algorithms [5], [8] this approach is different in three main areas.

1. Using TV model [9] latent image is divided into two components- cartoon and texture components. For orientation estimation texture component is used.
2. To reduce computation time, this method uses sparse coding model [9] to reconstruct the orientation field. Whereas in other method entire dictionary is searched in order to get the best patch.
3. Multiple dictionaries are constructed instead of fixed-scale dictionary for orientation estimation. Varying scales of patches are used for reconstruction.

In contrast to the algorithm [8], in this approach there is no need to estimate the pose information of latent fingerprint. Also due to the use of sparse coding, estimation of orientation field have achieved higher efficiency as compared to time consuming lookup in [5], [8].

In the approach proposed in [10] instead of using orientation patch dictionaries, ridge structure dictionaries are used for quality estimation and, orientation and frequency fields estimation. Despite of using smaller patch the identification accuracy of ridge dictionary is better as compared to global dictionary. This approach uses two stages for segmentation and enhancement- offline and online stages. Two types of dictionaries are learnt in offline stage.

1. A coarse-level dictionary [10] is used for coarse estimation of ridge with patch size of $64*64$ and
2. Sixteen fine-level dictionaries are created which have patch size of $32*32$ pixels. These are used for the purpose of estimation of ridge quality, and computation of orientation and frequency fields [10].

Two-step multiscale patch based algorithm is proposed in [11] which latent fingerprint enhancement is done using both ridge and minutia dictionaries.

In this approach latent image is represented as a 2D amplitude and frequency modulated (AM-FM) signal [11].

The minutiae are represented using spiral phase and ridges using continuous phase. In case of gabor dictionary only continuous phase is present because of which minutiae are not restored perfectly. So in order to overcome this limitation an approach is introduced in this paper in which a minutia dictionary is constructed by incorporating spiral to gabor dictionary. Advantage of using this approach is that it decreases the number of wrong minutiae which is achieved because of more accurate minutiae localization.

Limitation of using gabor function is that it cannot capture the minutia details that is the end point of ridges [11].

It is important to note that ridge structure dictionary and orientation patch dictionary do not perform well when a latent and background noise overlaps.

D. Gabor dictionary based approach

A set of Gabor basis functions are used in construction of redundant dictionary as presented in [12]. These functions capture the periodic nature of fingerprint regions due to which they are used to model local patches of latent image. By changing the values like frequency, patch size, initial phase angle etc of gabor function, dictionary is created.

Using set of gabor elementary functions dictionaries are created as proposed in [13]. In order to extract ridge features, multiscale patch-based sparse representation is repeatedly used in order to retrieve fingerprint samples. Basis atom of dictionary is created using gabor functions. Sparse representation is further used for reconstruction of texture component. One of the most important parameter for fingerprint reconstruction using sparse representation is the patch size. Ridge structure details are conserved in small patches while suppression of noise is better in large patches.

To preserve both the properties an approach is proposed in which patch size is gradually increased along with dictionary scale for reconstruction of latent images. This approach is robust and preserves details. The first step proposed in this approach is to create dictionary atom using gabor functions. This approach is highly adaptive and fast in its implementation. It is said to be adaptive because if the patch size is varied.

A dictionary construction method using the sparse representation on the Gabor dictionary is presented in [14]. In this approach low reliable fingerprint regions are reconstructed using local gabor dictionary. For construction of dictionary, first sparse representation based on global gabor dictionary is calculated and then orientation field is estimated. In case of a corrupt patches, local dictionary is constructed by obtaining orientation field from good patches. The image is reconstructed finally by applying sparse representation on the local dictionary. Fingerprint enhancement in this approach is modeled as reconstruction and sparse representation problem. In order to get good results dictionary should contain all types of ridge details and structures.

Some authors also constructed their dictionary using hybrid approach as presented in [15]. The dictionary in this approach was constructed by combining localized and ridge dictionary.

In Table1, comparison of existing dictionary based approaches for latent fingerprints is presented. It helps to gain insight about advantages and limitations of dictionary construction approaches.

III. DATABASES AVAILABLE

Various databases available related to latent fingerprints are as follows:

A. NIST SD27

This database is a collection of grayscale fingerprint images which contain 258 samples. Dataset includes both 500 pixel per inch (PPI) and 1000PPI samples. It can be used for rolled fingerprint matching.

B. WVU latent databases

It contains 449 images which are not publicly available database but it contains exemplars of 500 and 1000 PPI. Manually marked features are available and the database can be used for latent to rolled fingerprint matching.

C. FVC 2004 databases

FVC is a collection of 1440 impressions. 120 fingers with 12 impressions per finger were used for its construction. DB1 and DB2 were collected using optical sensors. Thermal sweeping sensor were used for collection of DB3 whereas synthetic fingerprint generation sensors were used for DB4 databases.

D. IIT latent fingerprint database

This database is a collection of 15 subjects, in which for each subject there are 10 fingerprints. The gray scale images are scanned using 500PPI scanner. The size of each image is 4752*3168 pixel.

E. IIT Simultaneous Latent Fingerprint (SLF) database

Database contains simultaneous fingerprint of 15 subject. With plain tile as background fingerprint images are obtained using black powder technique.

F. Multisensor Optical and Latent Fingerprint database

The database contains 19,200 fingerprints samples. 100 subjects were used for construction of database using capture methods like Cross Match L-Scan Patrol, Secugen Hamster-IV etc.

G. IIITD Multi-surface Latent Fingerprint database (IIITD MSLFD)

IIITD MSLFD consists of 551 latent fingerprints samples which are captured at 500DPI using Cross Match L-Scan Patrol. Eight different surfaces are used for capturing fingerprints of 51 subjects. Surfaces like Ceramic mug, plate, Steel glass, book cover etc were used for fingerprint capturing.

H. Tsinghua Latent Overlapped Fingerprint database

The database is collected at 500PPI which can be used for testing of algorithms which separate overlapped prints. It consist of 12 plain fingerprints and 100 latent fingerprints which are overlapped. Optical fingerprint scanners are used to capture the dataset.

I. ELFT-EFS Public Challenge database

This database contain 1100 images which are captured using 500 and 1000PPI. Using this database level1, level2 as well as level3 features can be extracted.

Table 1: Comparison of dictionary based approaches for latent fingerprints

Approach	Ref	Objective	Description	Database	Limitation	Results
Global dictionary based approach	[5]	Enhancement	A single global dictionary is created for whole fingerprint.	NIST SD27	Ridge information is ignored. Dictionary creation and lookup is slow as compared to local approach	Rank-1 identification accuracy is 26% using VeriFinger SDK 6.2
Localized dictionary based approach	[6]	Matching	Fingerprints are aligned using orientation field dictionary by making use of large longitudinal database.	NIST SD27, NIST SD14	Exhaustive lookup of the dictionary required. Estimation of the pose information of latent fingerprint required, which increases complexity.	35% with NIST database (250K) 75% with (OK) K=overlapping factor
	[7]	Minutiae extraction architecture	A set of separate localized dictionaries for each location is created using concept of clustering Dictionary creation and lookup is faster as compared to global approach.	NIST SD27, FVC 2004	Dictionary maintenance is a challenge as for each location a separate dictionary of orientation patches is created.	NIST SD27: Precision =69.2%, Recall = 67.7%; FVC 2004: Precision = 79.0%, Recall = 80.1%
Ridge structure based approach	[9]	Reconstruction	Multiscale dictionaries and texture components are used. With orientation patches of varying scales Multiple dictionaries are constructed.	NIST SD27	Computation for false minutiae removal and repetitive minutiae removal is very high.	Average orientation estimation error (in degrees) is 16.38
	[10]	Segmentation and enhancement	Learning of ridge structure dictionaries is done directly from fingerprint patches.	NIST SD27 WVU latent databases	Dictionary created is able to deal with local noise. However detailed ridge information cannot be extracted from it.	Matching Performance with Ten print matcher 34.50% on NIST SD27, 50.33% on WVU DB. Performance with Latent Matcher75.58% on NIST SD27,
	[11]	Enhancement	Uses both ridge and minutia dictionaries for enhancement.	NIST SD27	Limitation of gabor function is that it cannot capture the minutia details that is the end point of ridges, bifurcations	Recall= 0.4916; Precision=0.3616
Gabor dictionary based approach	[12]	Enhancement	Local patch of fingerprint images are modeled using Gabor basis functions. By changing the values like frequency, patch size, initial phase angle etc. of Gabor function, dictionary is created.	FVC fingerprint databases	If parameters not selected carefully it can lead to distorted dictionary.	True positive rate is 0.7
	[13]	Enhancement	Gabor elementary functions are used for creation of basis	NIST SD27	Details of minutiae cannot be captured, which may result in missing and false	Identification accuracy is 26.8%

			atom for dictionary. For iterative reconstruction, Size of Patch size and scale of dictionary are gradually increased		minutiae.	
	[14]	Enhancement	Uses both local and global Gabor dictionary.	NIST SD27	Images distorted by the structured noises cannot be restored. Unclear ridge patterns are obtained due to display of weak texture image	Identification rate is around 70%

IV. CONCLUSION

The paper presents a review of dictionary based approaches for Latent Fingerprints. After reviewing the literature it is observed that dictionary based method is a widely used and efficient method for latent fingerprint reconstruction and enhancement. Each approach has its own strengths and its limitation, some of which can be addressed by using combination of various dictionary creation approaches, like combining localized dictionary with ridge based dictionary approach.

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