Robust Fingerprint Classification using an Eigen Block Directional Approach

P Madhusoodhanan Sumantra Dutta Roy
Department of Electrical Engineering, IIT Bombay, Powai, Mumbai - 400 076, INDIA
{pmadhu, sumantra}@ee.iitb.ac.in

Abstract

This paper describes a method of fingerprint classification using Eigen Block Directional Fingerprints. The method we propose dispenses off with the preprocessing stages such as segmentation, binarisation, thinning etc. We determine the block directional representation of a fingerprint and the location of the core points in a set of template fingerprints which belong to the same class. In the next step, we determine the most prominent eigen vectors of each template, which we term as the Eigen Block Directional Fingerprints. *To determine the classification of a fingerprint, we extract the Block Directional Fingerprint of the query image and determine the alignment parameters between the template and the query images using eigen tracker which minimises the robust error. We declare the class of the query image as the class of the Eigen Block Directional Fingerprint which result in the least robust error norm.*

1. Introduction

Fingerprints have been established and proved as one of the methods of uniquely identifying an individual due to fingerprints' characteristics of being unchangeable throughout his/her lifespan and its uniqueness. Various algorithms have been developed for recognition/matching of fingerprints. With the increase in size of the fingerprint databases being maintained, the search space/time recognition process increases. To reduce the search space and complexity, a systematic partitioning of the database into different class, termed as *classification* is adopted.

In this paper, we propose a novel method of robust fingerprint classification which categorises fingerprint images into four classifications, namely *Right loop*, *Left loop*, *Whorl* and *Arch* by determining the robust error norm, while projecting the query fingerprint image representation on the eigenspace of each of the set of classification template images representation.

Various researchers have developed a number of approaches for classification. However, there is no uniform acceptance of the total number of classes of fingerprints. For example, Karu and Jain [6] classify all fingerprints into six main categories as shown in Figure 1.

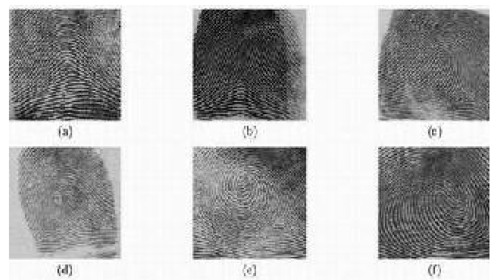


Figure 1. Types of fingerprints, as considered by Karu and Jain: (a) arch, (b) tented arch, (c) right loop, (d) left loop, (e) whorl, and (f) twin loop. This is Figure 1 in [7], page 390.

We broadly categorise the classification into two categories, namely, approaches based on local features and on global features. The former classify each fingerprint based on the relative positions of certain points which are derived from the information available within the neighbourhood of a pixel, with reference to each other. Kawagoe and Tojo [8] and Karu and Jain [7] classify the prints into five classifications by determining the number of singular points (cores and deltas and additionally, whorls in the former) and their relative positions with respect to each other. The success of this method depends crucially on the correct determination of the locations of the singular points, which depend on the quality of the image, the region of the finger which is imaged and the transformations (translation, rotation and shear) underwent by the print during imaging.

The classification approaches based on the global information classify the fingerprints based on the overall ridge flow pattern in the print. Since these methods do not rely on the singular points, they are less susceptible to noise introduced during the process of imaging. Fitz and Green [5] determine the Fourier Transform of the image and spectrum of the print and then employ a nearest neighbour classifier to categorise the print into four classifications. Chong *et al.* [4], use the estimated orientation field in a fingerprint for classification. They discriminate between the classes by analysing the global geometric shape of the fingerprints to categorise them in five classes. However, since a particular geometric feature may exist in more than one class, this approach fails in certain cases. To overcome the disadvantages present in both the approaches to classification, researchers use methods which are combination of these two. Shah and Sastry [10] combine the features of a line detector with SVM, nearest-neighbour and neural network classifier to categorize the prints into five categories.

It is important to note that the success of almost all existing approaches, in general, are crucially dependent on a proper alignment of the input fingerprints.

This paper is organised as follows. Section 2 brings forth the concepts and our implementation of a classification scheme in eigen imagespace. The results of the preliminary experiments are in Section 3. The conclusion and the path we intended to adopt in the future are in Section 4.

2. Eigenspace-based Fingerprint Classification

We propose a fingerprint classification scheme in an eigenspace of suitable features (we use block directional images for the purpose) which does not suffer from the limitations of the existing approaches of classification-based on local and global information contained in a fingerprint. Our scheme is robust to any parametric transformation (translation, rotation and shear) between the stored information about all classes of fingerprints and the query print presented to the classification system. *Classification in eigen image space is dependent on the general appearance of the fingerprint, independent of whether a particular feature is present or not.*

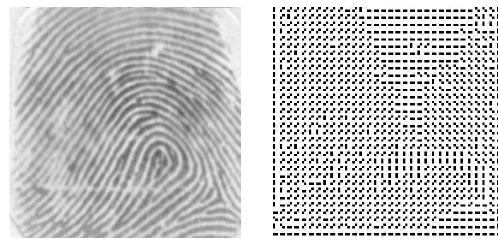
2.1 Eigen Block Directional Fingerprints

We represent the ridge flow pattern on the fingerprint by a block directional image. We then construct the block directional image of each fingerprint image in all the template sets and determine the eigenspace for each classification template set.

In the next step, we determine the core point which lies on the convex part of the ridges *i.e.*, the upper portion of the image. Various researchers report numerous approaches for determination of the core point. Our scheme to compute a block directional image embodies some ideas from the work of Karu and Jain [7] and Lee and Wang [9]. We calculate the direction at a pixel using the 9×9 mask shown in Figure 2. We add up the gray scale values in 8 directions at positions marked by $0, 1, \ldots, 7$ to get the slit sums $s_0, s_1, \ldots, s_7$. We then assign the direction with the maximum value of the slit

6		5		4		3		2
7		6	5	4	3	2		1
		7				1		
0		0				0		0
		1				7		
1		2	3	4	5	6		7
2		3		4		5		6

Figure 2. The 9×9 mask used by Karu and Jain. This is Figure 4 in [7], page 391.



(a) (b)

Figure 3. (a) A fingerprint image from the NIST database, and (b) its block directional image.

sum to the regions centred at a valley and the directions with the minimum value of the slit sum to the regions centred at a ridge. These directions give the directional image *D*, which we divide into blocks, to obtain the block directional image. The block directional image of an image from the NIST database [1] and its block directional image are as shown in Figure 3

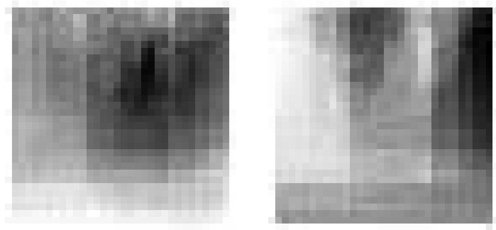
In a directional image *D*, which we derive, we observe that in a directional image, the blocks in the vicinity of the core have their directions as shown below

$$\begin{bmatrix} \mathrm{X} & D(i-1,j) & \mathrm{X} \\ \mathrm{X} & D(i,j) & \mathrm{X} \\ D(i-1,j+1) & \mathrm{X} & D(i+1,j+1) \end{bmatrix}$$

where $D(i-1,j) = 0°$, $D(i,j) = 0°$, $D(i-1,j+1) = 45°$ $D(i+1,j+1) = 45°$ and 'X' is don't care. The point $D(i,j)$ which satisfies the above condition and is the nearest to the bottom of the print is marked as the core.

An alternative method for determination of the block directional image and core point detection can also be is the method of Lee and Wang [9], which employs Gabor filters.

The presence of a number of fingerprints in the template increases the storage requirements. We overcome this increased dimensionality with the use of PCA. We use a template set consisting of 32 fingerprints from 4 fingers (8 prints per finger) for each of the four fingerprint classification. Some of these images are from the NIST database



(a) (b)

Figure 4. (a) The most and the (b) the second most prominent Eigen Block Directional Fingerprint of a left loop classification template image. The grey values correspond to a scaled encoding of the quantised set of directions in a block.

of fingerprint images and some were imaged in Indian Institute of Technology, Bombay. For each of the 32×32 sized block dimensional images fingerprint in the template set comprising of 8 images per finger, we construct a 1-D column vector with a dimension of 1024×1. We append 32 of these vectors to form a 1024×32 matrix. In the next step, we construct eigenspace for each template set, which we term as "Eigen Block Directional Fingerprints" by applying PCA to the block directional image ensemble. The Eigen Block Directional Fingerprints for each classification template, which correspond to the most prominent eigenvalues are stored. The two Eigen Block Direction Fingerprints which correspond to the two most prominent eigenvalues of a left loop template are as shown in Figure 4. In these images, we have arbitrarily assigned a grey value to each quantised direction in a block, and displayed the corresponding eigenvectors.

2.2 Construction of the Eigenspace

To construct an eigenspace, we use canonical images which are *aligned* and *are of good quality*. In the process of construction of the eigenspace of block directional images of a class of fingers, we encounter a number of prints which differ from prints of the same class due to intra-class variation. Hence, there is a need to learn and update the relevant eigenspaces, on the fly. Since a naive $\mathcal{O}(mN^3)$ algorithm (for N images having m pixels each) is time consuming, we use an efficient, scale-space variant of the $\mathcal{O}(mNk)$ algorithm (for k most significant singular values) of Chandrasekaran *et al.* [3].

2.3 Classification and Block Directional Eigen Fingerprints

A fingerprint image is a result of a transformation of a 3-D object (the finger ridges) to a 2-D plane. Though the ridge structure on a finger does not change, prints which are acquired from the same finger also have certain inter-print variation. These are due to noise introduced by imaging, dirt accumulated between the ridges, different regions of the finger being imaged and parametric transformations. The overall ridge flow in prints which are of the same class have certain intra-class variations for similar reasons. To overcome the intra-class differences and to have a template which caters for all possible variations, a large number of prints of a particular classification need to be imaged. The number of prints which are needed to represent all possible distortions is very high since the number of possible distortion is very high. This results in an increased storage area. However most characteristics in all the prints which belong to a same class are common. Hence the storage requirement for a template which represents all possible distortions in a class of print can be reduced. One method which has been used for dimensionality reduction is the the concept of *eigenspaces* [11], [2].

The universal set comprising of all fingerprint can be considered as an image space. The sets of all fingerprints which belong to a class can hence be considered as a subspace of the image space. Such a partitioning of the image space of fingerprints is possible due to the degree of variation between classes [4]. The universal set of fingerprints S can be given as $S = \bigcup_i p_i$ and $p_i \bigcap p_j = \delta_{ij}$, where p_s are the set of all fingers which belong to the same class. Similarly, all the prints imaged from a finger with all possible distortions may be considered as a subspace of the each classification subspace. Hence each fingerprint image can be considered as a point in the image space corresponding to a classification [11]. Conversely, a fingerprint can be considered to belong to a particular class, if it is a point in the subspace of a particular classification subspace. If image space of each classification can be represented by single points in the image space, the class of any fingerprint can be determined by a distance measure between the point representing it in the image space and the points representing every classification. Thus an eigenspace approach to the classification problem allows us to calculate the distance between the individual classes. A diagram representing this concept is as shown in Figure 5.

2.4 Robust Classification of Unaligned/Affinely Distorted Prints

Our classification scheme of a unaligned/affinely distorted query image follows the algorithm shown in Figure 6

In the first stage of classification, we determine the block directional image of a query fingerprint and the core point of the query image. The displacement between this and the core of a classification template gives the initial value of the translation parameters. We determine the initial value for

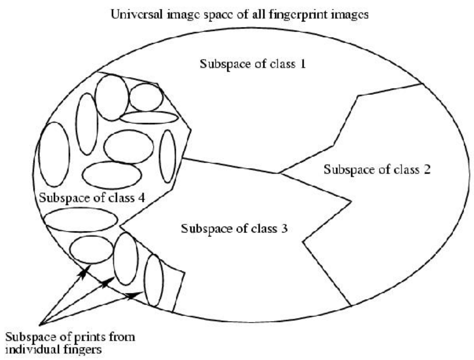


Figure 5. A schematic representation of the distribution of classes in the image space.

ALGORITHM classify_query

```
01. read query image
02. obtain directional image;
03. determine core point;
04. obtain initial estimate of translation
     parameters
05. obtain initial estimate of rotation
     parameters
06. determine exact parameters for
    alignment
07. align the query image
    with each template
08. estimate robust error norm for
    each class
09. declare class based on lowest
    robust error norm
```

Figure 6. The Classification Algorithm

the rotation parameter by estimating the principal axis of the print. We then calculate the initial estimate of the reconstruction coefficients by taking the projection of the block directional image of the query fingerprint on the eigenspace of block directional images of a classification.

We adapt an idea from Black and Jepson's EigenTracker [2] for this purpose. We pose the problem as finding affine transformation coefficients $\mathbf{c}$, such that the robust error function between the parameterized image $\mathbf{I}$ (indexed by its pixel location $\mathbf{x}$) and the reconstructed one $\mathbf{Uc}$ (where $\mathbf{U}$ is the matrix of the most significant eigenvectors) is minimum, for all pixel positions $\mathbf{x} = [x\ y]^T$:

$$arg\ min_{\forall \mathbf{x}}, \rho(\mathbf{I}(\mathbf{x} + \mathbf{f}(\mathbf{x}, \mathbf{a})) - [\mathbf{Uc}](\mathbf{x}), \sigma) \qquad (1)$$

Here, $\rho(x, \sigma) = x^2/(x^2 + \sigma^2)$ is a robust error function, and σ is a scale parameter. The 2-D affine transformation is given by

$$\mathbf{f}(\mathbf{x}, \mathbf{a}) = \begin{bmatrix} a_0 \\ a_3 \end{bmatrix} + \begin{bmatrix} a_1 & a_2 \\ a_4 & a_5 \end{bmatrix} \mathbf{x} \qquad (2)$$

We note that the above method requires non-linear optimisation, which needs a seed point. Steps 03 – 05 in the algorithm (Figure 6) describe the steps involved. The detection of the core point gives an estimate of the translational parameters, while a PCA performed on the image gives an estimate of rotational parameters. We thus have the initial affine parameters initialised to the values for an Euclidean transformation. (We have found this to suffice well for our experiments.) Iterating on the initial estimate of the affine parameters and the initial estimate of the reconstruction coefficients, we determine the optimum value of the affine parameters and reconstruction coefficients which minimise the robust error norm. We evaluate the robust error norm corresponding to the reconstruction of the query image with Eigen Block Directional Fingerprints of each classification. We declare the classification of the Eigen Block Directional Fingerprint, which results in the least robust error norm as the classification of the query image.

2.5 Extension to Fingerprint Matching and Recognition

We are currently in the process of extending the idea developed for fingerprint classification using Eigen Block Directional to fingerprint matching and recognition. The problem of matching and recognition can be posed as a problem of determining the distance between a representation of a query image (query block directional image) and the subspace of the image space which represents all the possible prints of a finger. The computational complexity of the problem is reduced as the eigenspace approach for determination of the image space and alignment serves as a common thread in the classification problem and the matching/recognition problem

3. Results

We have applied this approach to fingerprints captured using a fingerprint scanner as also some fingerprint images from NIST database. Preliminary experiments with a limited database consisting of freely downloadable fingerprint images from NIST and some locally acquired images show encouraging results. We have used the Hamster© fingerprint scanner manufactured by NITGEN Biometric Solutions to build up a local database of fingerprints locally for building the database. Our training set consists of 32 images per classification. Since the "Tented Arch" class was not available in the NIST free database nor in our locally built database, we have restricted our classification to four classes, namely *Right Loop, Left Loop, Whorl* and *Arch*. In order to verify the efficacy of our classification scheme, we have tested our approach on 42 fingerprint images. The results are tabulated in Table 3, where the actual classification

(a) (b)

Figure 7. Prints which were classified as (a) an arch due to insufficient information, and (b) a left loop due to leftward inclination of the whorl.

(a) (b)

Figure 8. (a) A print from NIST database rotated by a certain angle and (b) the print translated and rotated to align with the template.

distribution of the prints are depicted along the horizontal direction and the results of our scheme are depicted along the vertical direction.

	L loop	R loop	Whorl	Arch	Unknown
L loop	9	0	3	0	0
R loop	0	7	1	0	0
Whorl	0	1	12	0	0
Arch	0	0	1	7	1

Table 1. Experimental Results

One print whose classification is ambiguous is classified as belonging to "arch", since sufficient information regarding its classification is not available in the part of the print imaged. This image is as shown in Figure 7(a). It is quite evident that this print's position in the imagespace would be closer to the space of images of the class "Arch". We observe out of 17 prints of type "arch", 5 are classified wrongly due to the axis of the central part of the print around the core showing a left or right tilt. One of the prints is shown in Figure 7(b). We observe that in the case of this print, the robust error norm calculated taking the projection on the Eigen Block Directional Fingerprints of the left loop and whorl classes differed by a margin of 0.05%. We plan to overcome this error by increasing the number of fingerprints from which the eigenspace of each class is constructed.

A correctly classified print is shown in Figure 8a. The initial estimate of affine parameters for the print were : translation in X axis = 20 pixels, translation in Y axis = 76 pixels and angle of rotation = 4° and its corresponding block directional image were translation in X axis = 2 pixels, translation in Y axis = 9 pixels and angle of rotation = 4°. The optimised parameters were : translation in X axis = 24 pixels, translation in Y axis = 72 pixels and angle of rotation = 5°. The robust error obtained for the correct classification (left Loop) for a translation-aligned image was about 20% less than that of the next nearest classification and for a translation and rotation aligned image, this was about 40% less than the nearest classification. We have found Euclidean estimates as the initial seed values of the affine parameters - to suffice well for our experiments. Scope for future work includes experimenting with cases when a core point is missed out, or where one has spurious cores - this will give an estimate of the breakpoint of the proposed method.

4. Conclusions and Future Work

In this paper we describe some preliminary experiments for classification of fingerprints using Eigen Block Directional Fingerprints. We the use of concept of eigenspaces which has been widely used in appearance based recognition systems, tracking, face recognition etc for fingerprint classification. After preliminary investigation, we observe that this has resulted in good results in classification. This scheme's reduced dependence on the local information in the and increased dependence on the global information makes it robust to deformities due to imaging. Our use of eigen tracker to align the query image ensures that the scheme is robust for all parametric transformation (translation, rotation and shear) between fingerprints belonging to the same classification. Our current work includes testing of our classification scheme using the complete NIST database and extension of the scheme to include the class "Tented Arch" also. We are also in the process of extending this scheme to robust fingerprint matching and recognition.

5. Acknowledgments

The authors gratefully acknowledge the assistance of the Department of Science and Technology (DST), Government of India for the project awarded to the last author, "Automated Fingerprint Analysis and Recognition" (No. SR/FTP/ET-199/2001) under the SERC FAST TRACK PROPOSAL FOR YOUNG SCIENTISTS (2001-2002) - (ENGINEERING SCIENCES), Science and Engineering Research Council, Department of Science and Technology.

References

[1] http://www.nist.gov/srd/nistsd4.htm.

[2] M. J. Black and A. D. Jepson. EigeniTracking: Robust Matching and Tracking of Articulated Objects using a View-based Representation. *Intl. Journal of Computer Vision*, 26(1):63 – 84, 1998.

[3] S. Chandrasekaran, B. S. Manjunath, Y. F. Wang, J. Winkeler, and H. Zhang. An Eigenspace Update Algorithm for Image Analysis. *Graphical Models and Image Processing*, 59(5):321 – 332, September 1997.

[4] M. M. S. Chong, T. H. Ngee, L. Jun, and R. K. L. Gay. Geometric Framework for Fingerprint Image Classification. *Pattern Recognition*, 30(9):1475 – 1488, 1997.

[5] A. P. Fitz and R. J. Green. Fingerprint Classification using Hexagonal Fast Fourier Transform. *Pattern Recognition*, 29(10):1587 – 1597, 1996.

[6] A. K. Jain, S. Prabhakar, and S. Pankanti. Matching and Classification: A Case Study in Fingerprint Domain. *Proc. Indian National Science Academy*, 67(2):223 – 241, 1999.

[7] K. Karu and A. K. Jain. Fingerprint Classification. *Pattern Recognition*, 29(3):389 – 404, 1996.

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

[9] C.-J. Lee and S.-D. Wang. A Gabor Filter-Based Approach to Fingerprint Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 000:371 – 378, 1999.

[10] S. Shah and P. S. Sastry. Fingerprint Classification Using a Feedback-Based Line Detector. *IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics*, 34(1):85 – 94, 2004.

[11] M. Turk. A Random Walk through Eigenspace. *IEICE Transactions on Information and Systems*, E84-D(17):1586 – 1595, 2001.