Fingerprint Analysis via Oriented Band Pass Filters

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A new fingerprint image representation which captures both the local features such as minutiae and the global features such as overall ridge structure is presented. The basic tool is a set of oriented band pass filters which are parametrized by three parameters. We relate quantitative filter responses to the structural characteristics of the fingerprint ridges.

1 Introduction

The inner surface of a finger is covered with a pattern (Figure 1) which is unique for each individual, enabling the use of fingerprint image as a means of identifying a person. Automated identification and verification of fingerprint images play a very important role in security applications when an access to a facility need to be controlled.

Fingerprint analyses are based on overall shape of ridge curves i.e curvature of the ridge curves and certain local features called minutiae. Minutiae points are the singularities of the fingerprint ridges. Most typical minutiae are the bifurcation points where a ridge splits into two ridges, and the termination points where a ridge ends.

In literature several approaches to fingerprint analysis have been proposed. Mostly, these approaches are comprised of a couple of modules which transform input fingerprint image first to a binary image and then to a ridge representation. Points of interest e.g. minutiae are detected from the ridge representation [5]. Binarization process is not only time consuming but more importantly it may cause a loss of significant information while retaining irrelevant details. Recently algorithms for detection of ridges directly from raw fingerprint images are presented in [1, 4]. In ridge representation necessary information is implicit. Features such as minutiae still need to be extracted. On the other hand minutiae representation alone fails to describe overall ridge pattern.

We transform raw fingerprint image into a representation where both the localized features such as bifurcation points and the information about overall ridge structure is captured. This paper describes our preliminary results.

2 The Approach

Our approach is based on utilization of a set of Gabor like oriented filters which are parametrized by three parameters which determine the filter orientation, spatial frequency and filter width respectively. The filters are obtained by multiplying a cosine function with an elongated Gaussian, thus, the filters are band pass in one direction and low pass in the orthogonal direction.

At the finest scale (scale=0), we require that the filter extend from one valley point to the next consecutive valley point in the band pass direction. Thus the standard deviation of the elongated Gaussian in the band pass direction should be equal to the $1/6^{th}$ of the peak to peak pixel size. At scale s the standard deviation increases by a factor of $2s+1$. The standard deviation in the low pass direction is taken to be the double.

Consequently, a filter $F^{\Theta,W,s}$ at a given orientation, spatial frequency and scale is given by

$$\begin{aligned} F &= \left\{ \frac{1}{4\pi\sigma_x^2} e^{\left(\frac{(x\cos\Theta + y\sin\Theta)^2}{-2\sigma_x^2} + \frac{(-x\sin\Theta + y\cos\Theta)^2}{-8\sigma_x^2} \right)} \right\} \\ &\times \; cos(2\pi W(x\cos\Theta + y\sin\Theta)) \end{aligned} \tag{1}$$

where

$$\sigma_x = (2s+1)/(6W)$$

Filter response $R^{\Theta,W,s}$ for a given image is the convolution of the image with $F^{\Theta,W,s}$. A sample set of filters at scale=0 and the filter responses obtained for the sample image are shown in Figures 2 and 3 respectively.

Our goal is to relate quantitative filter responses, in the 3D response space, to the structural features.

2.1 Normalized Response

Filter response at a point is maximized when the filter orientation matches to ridge orientation and the spatial frequency of the filter matches the ridge width. Normalized response N^s at a given scale s is defined as follows:

$$N^s(x,y) = \max_{\Theta,W} R^{\Theta,W,s}(x,y) \qquad (2)$$

This process normalizes the response with respect to scale and pose changes. Scale parameter determines the filter width, thus the detail level at which the analysis to be performed. At each scale, we define orientation and spatial frequency maps as the values of orientation and scale which yield the maximum response. We expect that both the orientation and spatial frequency maps will be smooth except certain locations. These locations are either the minutiae or the extremum points of the ridge curves.

3 Illustrative examples

A synthetic image and the corresponding orientation map is shown in Figure 4. The orientation map is smooth except at the ridge corners. Figure 5 shows the orientation map for a section of the sample image at three scales. When scale is 0, there are too many points of abrupt change. As the scale gets coarser orientation map becomes smoother. Among three sample points only the leftmost point which is a true bifurcation has an orientation discontinuity at scales above 0. For a sample image, the locus of the points with an orientation change is shown in Figure 6. Figure 7 displays the same loci for a rotated image.

4 Issues

One of the most important issues in our approach is the discretization of the parameter space. In our initial experiments we used filters at 8 equally spaced directions. The values for the spatial frequency is chosen manually and it reflects the scale of the original image. To elaborate, if the peak to peak pixel size varies between a and b, the spatial frequency values are sampled from the interval $\left[\frac{1}{b}, \frac{1}{a}\right]$.

Number of filters at different spatial frequency values are not very large and the determination of the correct spatial frequency values may be done automatically from a small window in the image. However, the discretization of the orientation space is quite critical. For example, instead of rotating the image by 22 degrees (which is very close to 22.5), if we rotate it by 30 degrees, the result may not preserve the invariance. Of course, if we sample the filter orientation at 10 degrees apart, rather than 22.5, the problem will be solved. However, it is computationally very expensive to compute the filter response for each possible value of the parameter set.

Following the work of Freeman and Adelson [2], a concept called steerable filters received attention. The basic idea is to compute a set of "basis filters" at selected parameter values and to compute the rest of the filters as the linear combination of the basis filters. Since the convolution operation is linear, it is possible to express the filter response at any parameter value as the combination of the basis responses.

Recently a concept of "approximate steerability" is introduced for functions (filters) which are not steerable and methods for computing best steerable approximation is presented [3, 6]. It is possible to use these methods to exhaustively discretize the rotation parameter space.

A second issue is the relative weakness of the method in catching end points compared to catching bifurcation points. A quite simple solution is to reverse the image and perform the same operation, since the end points are the bifurcations of the valleys.

5 Conclusions and Future Work

A new way of representing fingerprint images for analysis purposes is presented. The representation captures both the minutiae and the overall ridge pattern. We utilized oriented band pass filters and give the relation between the quantitative filter response and the ridge patterns. The difficulty arise in discretizing the parameter space and we proposed the use of approximate steerability to solve the problem.

We are developing a method for computing steerable approximation for our filter using a polynomial approximation and neural networks. It is also possible to use group theoretical method presented in [6].

References

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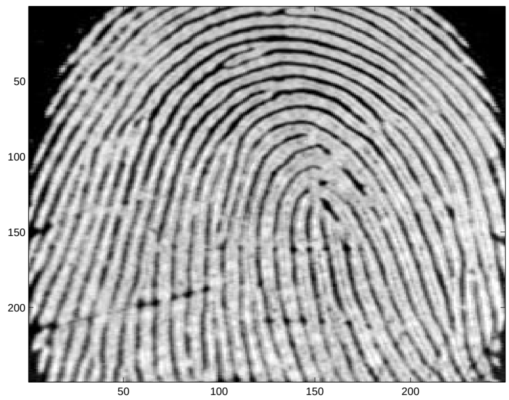

Figure 1: Sample fingerprint image

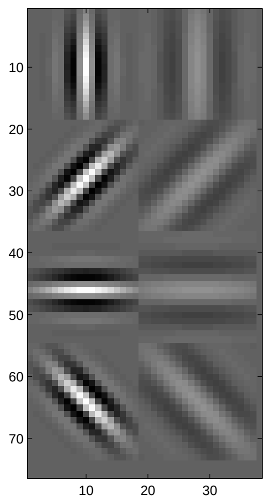

Figure 2: A sample set of filters at scale 0.

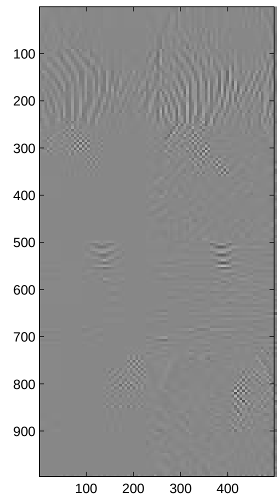

Figure 3: The corresponding responses for the sample image.

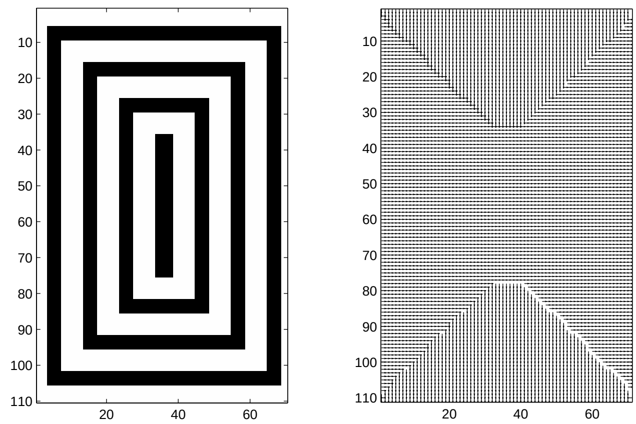

Figure 4: A synthetic image and its orientation map

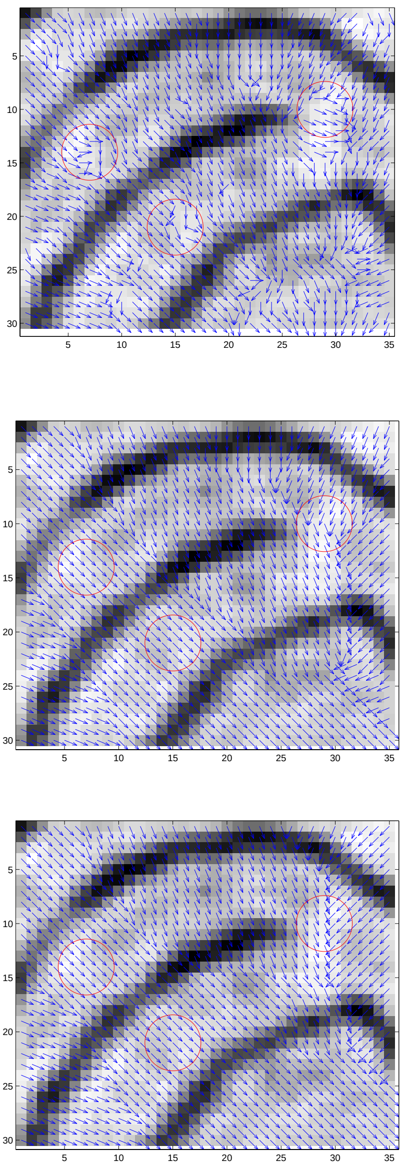

Figure 5: Orientation maps in a sub image at three scales. Top image is the map at scale= 0, left image on the bottom is at scale= 1 and the right image on the bottom is at scale= 2. Light areas are the fingerprint ridges. At scale= 0, there are many points of abrupt orientation changes. As the scale gets coarser orientation map becomes smoother. Among three sample points only the leftmost point which is a true bifurcation has an orientation discontinuity at scales above 0.

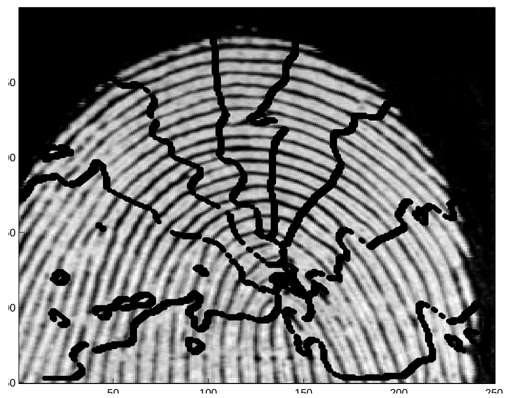

Figure 6: Sample image and its representation.

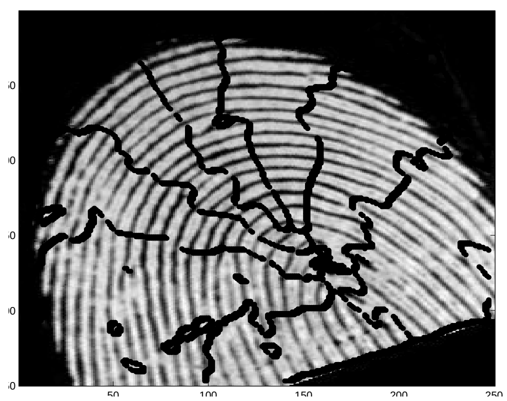

Figure 7: Rotated image by 22 degrees and its representation