FINGERPRINT IDENTIFICATION USING MODIFIED GABOR FILTER

Ratnadewi, Didi Sugianto
Dept. of Electrical Engineering, Maranatha Christian University
Jl. Prof. Drg. Suria Sumantri 65, Bandung 40164, Indonesia
Phone: +62+22 2012186, Fax: +62+22 2017622
e-mail: rdewi@bdg.centrin.net.id; ratnadewi@engineer.com

ABSTRACT

Fingerprints have been used as biometrics for personal identification or verification since a century ago. Although no exactly the same fingerprint from distinct identities was found, a perfect system for automatic fingerprint identification does not exist. The technique described here obviates the need for extracting minutiae points to match fingerprint images. This paper implements a Modified Gabor Filter (MGF). A circular tessellation of filtered image is then used to construct the ridge feature map. The fingerprint matching is based on the Euclidean distance between two corresponding feature vectors. This method can lessen noise, improving contrast between ridge and valley and also have tolerance to translation and rotation. Our system can increase the quality of image fingerprint. The achievement rate percentage of recognition is 85%.

Keywords: *Biometrics, Modified Gabor filters, fingerprints, matching.*

1. INTRODUCTION

Fingerprint-based identification is one of the most important biometric technologies which has drawn a substantial amount of attention recently. Humans have used fingerprints for personal identification for centuries and validity of fingerprint identification has been well established. In fact, fingerprint technology is so common in personal identification that it has almost become the unique across individuals and across fingers of the same individual. Even identical twins having similar DNA, are believed to have different fingerprints. These observations have led to the increased use of automatic fingerprint-based identification in both civilian and law-enforcement applications[1].

In most automatic fingerprint identification systems, the representation of fingerprints is based on minutiae such as ridge ending and ridge bifurcation, with each minutia being characterized by its locations and orientation. With this representation, the matching problem is reduced to a point pattern-matching problem. In the ideal case described by Jain[2], the matching can be accomplished by simply counting the number of spatially overlapping minutiae. But in practice, the sensing system maps the three-dimensional finger on to two-dimensional images. Once the location, pressure and direction of impression change, the mapping will change accordingly, which inevitably leads to nonlinear deformation of fingerprint images.

Two fingerprint images may have translation, rotation or even nonlinear deformation between them. If the time span between two impressions is long, the images may also change due to cuts on finger or skin disease.

In most systems, fingerprint is represented with a set of minutiae that is called template. The representation itself may be noisy due to presence of spurious minutiae and absence of genuine minutiae. Also, the properties of minutiae such as the location and orientation may be inaccurately estimated due to image degradation and imperfect preprocessing[3].

This paper implements a Modified Gabor Filter (MGF). A circular tessellation of filtered image is then used to construct the ridge feature map. The fingerprint matching is based on the Euclidean distance between two corresponding feature vectors.

2. FINGERPRINT MATCHING

A fingerprint is the pattern of ridges and furrows on the surface of a fingertip. Ridges and valleys are often run in parallel and sometimes they bifurcate and sometimes they terminate. The important features known as minutiae can be found in the fingerprint patterns. Minutiae means small details and this refers to the various ways that ridges can be discontinuous. A ridge can suddenly come to an end which is called termination or it can divide into two ridges which is called bifurcations (see Figure 1)[4]

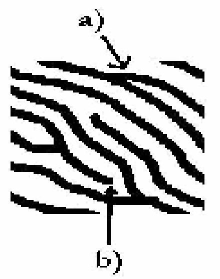

Figure 1. An example of a) bifurcations and b) ridge endings

The ridge structure in a fingerprint can be viewed as an oriented texture patterns having a dominant spatial frequency and orientation in a local neighborhood. The frequency is due to inter ridge-spacing present in a fingerprint and the orientation is due to the flow pattern exhibited by ridges. Most textured images contain a narrow range of spatial frequencies. For a typical fingerprint images scanned at 500 dpi, 8 bit grayscale, there is a little variation in the spatial frequencies among different fingerprints. This implies that there is an optimal scale (spatial frequency) for analyzing the fingerprint texture[1].

The proposed scheme first detects the core point. A circular region around the core is located and tessellated into 36 sectors. The spatial tessellation of fingerprint image which consists of the region of interest is defined by collection of sectors. We use three concentric bands around the core point. Each band is 20 pixels wide and segmented into twelve sectors. Thus we have a total of 12 x 3 = 36 sectors and the region of interest is a circle of radius 12 pixels, centered at the core point.

The pixel intensities in each sector are normalized to a constant mean and variance. Normalization is performed to remove the effects of sensor noise and gray level background due to finger pressure differences. For all the pixels in sector *Si*, where i $\in$ (0, 1, 2, …, 35), the normalized image is defined as[1]:

$$Ni(x,y)=\begin{cases} M_o+\sqrt{\dfrac{V_o\times(I(x,y)-M_i^2)}{V_i}}, & if \quad I(x,y)>M_i \\ M_o-\sqrt{\dfrac{V_o\times(I(x,y)-M_i^2)}{V_i}}, & otherwise \end{cases} \tag{1}$$

Mi and *Vi* are estimated mean and variance of gray levels in sector *Si* respectively. *Mo* and *Vo* are desired mean and variance values, respectively. For our experiments, both *Mo* and *Vo* are set to a value of 50.

Gabor filters optimally capture both local orientation and frequency information from a fingerprint image. An even symmetric Gabor filter has the following general form in the spatial domain[5]:

$$G(x,y;f,\theta)=\exp\left(-\frac{1}{2}\left[\frac{x'^2}{\delta_{x'}^{\,2}}+\frac{y'^2}{\delta_{y'}^{\,2}}\right]\right)\cos(2\pi fx') \tag{2}$$

$$x'=x\sin\theta+y\cos\theta \tag{3}$$

$$y'=x\cos\theta-y\sin\theta \tag{4}$$

Where f is the frequency of the sinusoidal plane wave along the direction θ from the x-axis, and $\delta_{x'}$ and $\delta_{y'}$ are the space constants of the Gaussian envelope along x and y axis, respectively. The frequency f is the average ridge frequency (1/K), where K is the average inter ridge distance. The average inter ridge distance is approximately 10 pixels in a 500 dpi fingerprint image. Hence, f=1/10. Eight different orientations are examined. These correspond to θ values of 0, 22.5, 45, 67.5, 90, 112.5, 135, 157.5 degrees. The values for $\delta_{x'}$ and $\delta_{y'}$ were empirically determined and each is set to 4.

Let $F_{i\theta}(x,y)$ be the θ direction filtered image for sector Si. Now, for i $\in$(0, 1, 2, …, 35) and θ $\in$(0, 22.5, 45, 67.5, 90, 112.5, 135, 157.5 degrees) the feature value, $V_{i\theta}$, is the average absolute deviation from the mean defines as[1]:

$$V_{i\theta}=\frac{1}{n_i}\left[\sum_{n_i}\left|F_{i\theta}(x,y)-P_{i\theta}\right|\right] \tag{5}$$

Where n_i is the number of pixels in S_i and $P_{i\theta}$ is the mean of pixel values of $F_{i\theta}(x,y)$ in sector Si. The average absolute deviation of each sector in each of the eight filtered images defines the components of our 288 dimensional feature vector.

The rotation invariance is achieved by cyclically rotating the features in a feature vector itself. A single step cyclic rotation of the features corresponds to a feature vector which would be obtained if the image was rotated by 11.25 degrees.

Fingerprint matching is based on finding the Euclidean distance between the corresponding feature vectors. This minimum score corresponds to the best alignment of the two fingerprints being matched. If the Euclidean distance between two feature vectors is less than a threshold, then the decision that “the two images come from the same finger” is made, otherwise a decision that “the two images come from different fingers” is made. Since the template generation for storage in the database is an off-line process, the verification time still depends on the time taken to generate a single template.

3. EXPERIMENTAL RESULTS

In this experiments the fingerprint images can be processed with this step, there are the original image, detects the core point, crop image, circular tessellation, normalization image, filterization image, feature vector image (see Figure 2)

Figure 3 described that the same fingerprint image with translation and rotation, after the process the feature is almost the same.

Figure 4 described the feature result for four person fingerprint.

After the code process from feature vector, the code result is stored in database fingerprint file. Table 1. is the Euclidean distance values for all fingerprint images include translation and rotation fingerprint with T_1=12 and T_2=10.

In table 2, the match fingerprint is the fingerprint with minimum Euclidean distance but still under threshold. For this experiment the threshold is 200000.

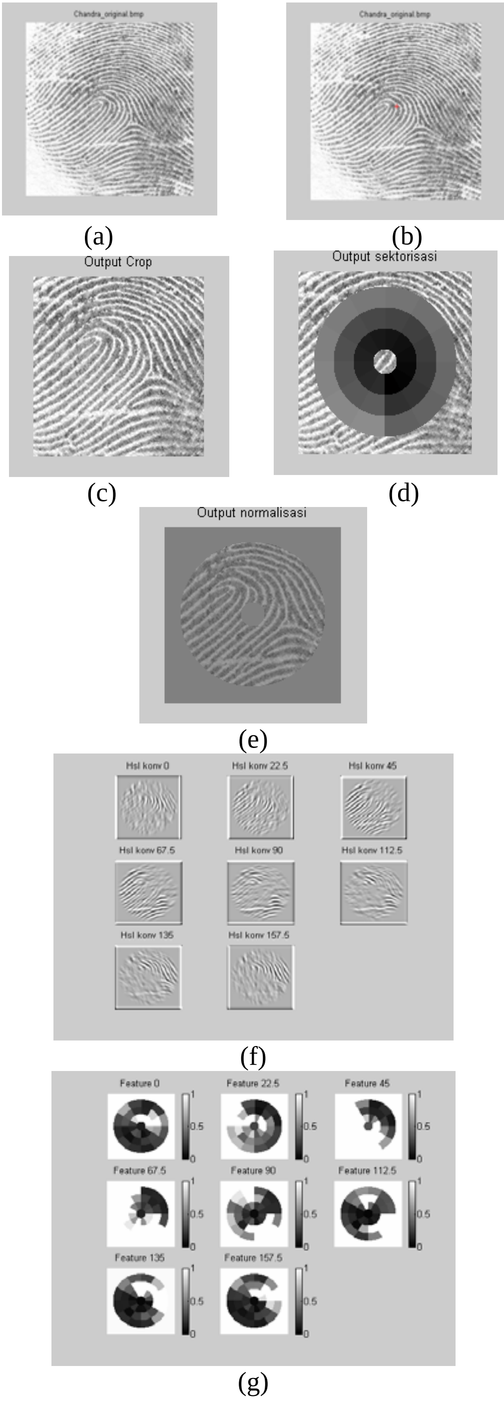

Figure 2. (a) original image (b) detects the core point (c) crop image (d) circular tessellation (e) normalization image (f) filterization image (g) feature vector image.

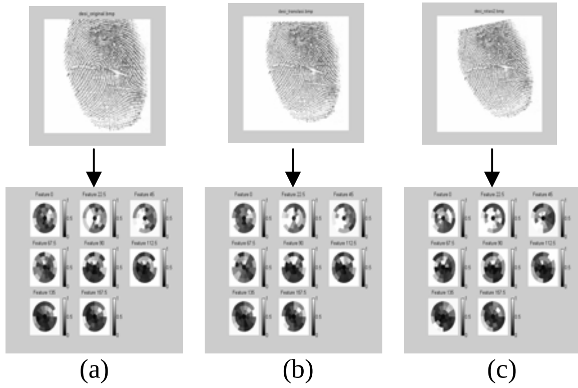

Figure 3. Feature experimental result for the same fingerprint (a) Original, (b) after translation (c) after rotation

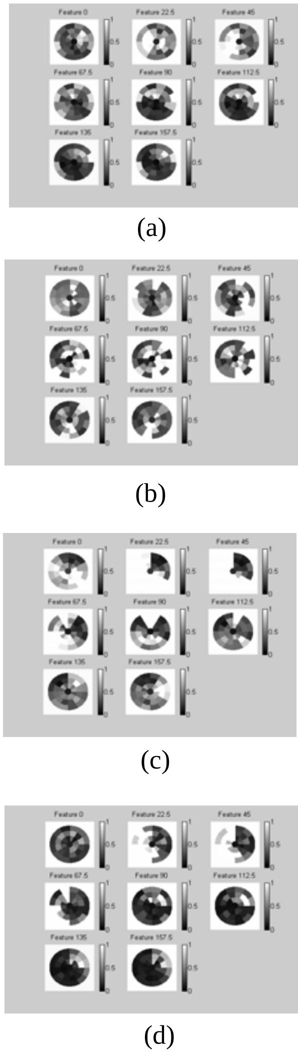

Figure 4. Feature experimental result for the different fingerprint (a) Desi, (b) Didi, (c) Ferry and (d) Yuni fingerprint

Table 1. The Euclidean distance ($x10^5$) with T_1=12 and T_2=10 for fingerprint matching

	Chandra _original	***Desi_ original***	***Didi_ original***	***Ferry_ original***	***Yuni_ original***
Chandra original	0	4.7678	4.8999	4.8859	5.1507
Chandra translation	0.2836	4.8646	4.9895	4.9559	5.2505
Chandra rotation	0.1790	4.3581	5.0278	4.3694	4.5633
Desi original	4.3717	0	2.7049	3.9730	2.5063
Desi translation	4.3665	0.8735	2.7733	3.9126	2.6594
Desi rotation	4.6665	1.8289	2.8572	3.8488	2.5176
Didi original	5.0893	2.6756	0	4.0079	3.3420
Didi translation	5.1870	2.7313	0.5770	4.0852	3.4025
Didi rotation	4.8953	2.6936	0.3084	3.7822	3.1232
Ferry original	4.3771	3.9730	3.8022	0	3.5649
Ferry translation	4.3109	3.9707	3.7980	1.3276	3.6451
Ferry rotation	4.6321	3.9353	3.7755	0.9987	3.6116
Yuni original	4.5777	2.5063	3.4808	3.5649	0
Yuni translation	4.6055	2.4990	3.4490	3.5791	0.1942
Yuni rotation	5.1391	2.6266	3.1931	3.9342	1.1991
Andrian original	5.3551	4.7015	4.5169	4.1529	5.0068
Gaga original	5.0341	2.1279	2.3921	4.1839	2.7964

Table 2. The result of fingerprint matching

File name	***Similar with Database***	***Euclidean distance ($x 10^5$)***
Chandra original	Chandra	0
Chandra translation	Chandra	0.2836
Chandra rotation	Chandra	0.1790
Desi original	Desi	0
Desi translation	Desi	0.8735
Desi rotation	Desi	1.8289
Didi original	Didi	0
Didi translation	Didi	0.5770
Didi rotation	Didi	0.3084
Ferry original	Ferry	0
Ferry translation	Ferry	1.3276
Ferry rotation	Ferry	0.9987
Yuni original	Yuni	0
Yuni translation	Yuni	0.1942
Yuni rotation	Yuni	1.1991
Andrian original	Not matched	-
Gaga original	Not matched	-

4. SUMMARY

Implementation of Modified Gabor Filter (MGF) have been presented in this paper. A circular tessellation of filtered image is then used to construct the ridge feature map. The fingerprint matching is based on the Euclidean distance between two corresponding feature vectors. This method can lessen noise, improving contrast between ridge and valley and also have tolerance to translation and rotation. Our system can increase the quality of image fingerprint. A 85% recognition rate is achieved.

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