# A Novel Approach for Extracting Fingerprint Features from Blurred Images

**R. Vinothkanna, Amitabh Wahi**

***Abstract:- Biometrics is the science and technology of authentication by identifying the living individual's physiological or behavioral attributes. Fingerprint identification is one of the most well known and published biometrics. Normally in blurred fingerprints the extraction of ridges becomes very difficult. But the extraction of valleys instead of ridges from the same blurred fingerprint images will produce better results. In this paper, we have tried the extraction of features with different types of filters like Median filter, Gaussian filter, Wiener filter, Kalman filter and Gabor filter. We noticed that the extraction of valleys instead of ridges from blurred fingerprints will produce more features for forth coming processes like post-processing and matching process.***

***Index Terms:- Biometrics, Fingerprints, Valley Extraction, Ridge Extraction, and Gabor filter.***

## I. INTRODUCTION

The recent advances of information technologies and the increasing requirements for security have led to a rapid development of automatic personal identification systems based on biometrics. Biometrics refers to accurately identifying an individual based on his or her distinctive physiological (e.g., fingerprints, face, retina, iris) or behavioral (e.g., gait, signature) characteristics. It is inherently more reliable and more capable in distinguishing between an authorized person and a fraudulent imposter than traditional token-based or knowledge based methods.

Among all the biometrics, fingerprint recognition is one of the most reliable and promising personal identification technologies. Fingerprints are graphical flow-like ridges and valleys present on the surface of human fingers [1, 2]. They are widely used for personal identification in many commercial, civilian, and financial applications [3]. We propose to use the valley instead of the ridge for minutiae extraction. We use valley endings and valley bifurcations as fingerprint minutiae. Ridges are generally used for minutiae extraction, since most previous researches assume that the ridges and valleys in the fingerprint have a similar width and are equally spaced. In fact, this may not always be true for various fingerprints collected by different sensors. For example, the fingerprint images we collected using an optical sensor show that the average ridge width(typically six pixels) is thicker than the average valley width (typically three to four pixels), as illustrated in Fig. 1. Since a thinner binary image is easier for skeleton computation, we propose to use the valley instead of the ridge for minutiae extraction. We use valley endings and valley bifurcations as fingerprint minutiae. After the valley skeleton is extracted from the binary image, ideally, the width of the skeleton should be strictly one pixel. However, this is not always true, especially at the intersection points, thus producing spurious minutiae points. Fig. 2 shows the detailed characteristics of fingerprint features used in the automatic classification and minutiae extraction [4].

**Fig.1**


**Fig.2**

**Fig.1. Fingerprint images acquired using an optical fingerprint sensor (black areas: ridges; white areas: valleys). Fig.2. Fingerprint Characteristics.**

In this paper, we have analyzed our work with blurred fingerprint images. We have collected the blurred fingerprint images from the FVC 2000, FVC 2002 & FVC 2004 databases. We noticed that instead of extracting ridges, valley extraction provides more number of features. We have analyzed this concept with the help of various filters like Median filter, Gaussian filter, Wiener filter, Kalman filter and Gabor filter for extracting features. All the filters extracted more number of valleys when compared to ridges for the same fingerprint image. If more number of features is extracted with blurred and damaged fingerprint images, then there will be an advantage of time reduction because no enhancement techniques are needed.

The paper is organized into the following sections. Section 2 discusses about Preprocessing and Feature Extraction. Post processing is discussed in Section 3. Section 4 discusses about Matching followed by the Conclusions and Future work is discussed in Section 5.

## II. PREPROCESSING & FEATURE EXTRACTION

A critical step in an automatic fingerprint identification system (AFIS) is reliably extracting features from the input fingerprint images. The skeleton based method generally consists of the following main steps:

1) Use an adaptive thresholding algorithm to compute the binary image from the input gray scale fingerprint image [5].

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2) Use a thinning algorithm to compute the fingerprint skeleton from the binary image [6,7].
3) Use a suitable filter to extract features from the skeleton of fingerprint image [8,9].
4) Post processing the minutiae set according to some heuristic rules [10].

The pre-processing of a fingerprint image comprises of procedures like, first the enhancement of image is done by histogram equalization. After this the process of binarization is done on the enhanced fingerprint image by using locally adaptive method. This binarized fingerprint image is segmented by using threshold or region of interest techniques [11]. By observation of the skeleton images and their corresponding binary images, it can be seen that the misconnections and the isolated regions (hole, dot, and island) in the binary images introduce a number of spurious minutiae in the skeleton images. The Binarization of fingerprint image is to convert an image up to 256 gray levels to white and black image. A locally adaptive binarization method is used in which image binarization is done by choose mean intensity value or threshold value and classify all pixels with or above threshold value as white and other pixels as black [12]. Separating the fingerprint area from the background is always useful to avoid extraction of noisy areas of fingerprint [13].

### *A. 2D Digital Filters*

The concept of Minutiae extraction (both ridges and valleys) of the fingerprint image can be extracted by any filter and the numbers of features are compared by us. Normally 2D digital filters are central to many image processing applications such as image enhancement, image deblurring, target matching etc. FIR (Finite Impulse Response) digital filters of the non recursive type can be realized by means of a simple hardware or software, and so mainly used for digital image processing [14].

In image processing, filters are mainly used to suppress either the high frequencies in the image that is smoothing the image, or low frequencies that is enhancing or detecting edges in the image. An image can be filtered either in the frequency or in the spatial domain. The first involves transforming the image into the frequency domain, multiplying it with the frequency filter function and retransforming the result into the spatial domain. The filter function is shaped so as to alternate some frequencies and enhance others. For example, a simple low pass function is l for frequencies smaller than the cut off frequency and 0 for all others [15].

The corresponding process in the spatial domain is to convolve the input image f(i,j) with the filter function h(i,j). This can be written as

$$g(i,j) = h(i,j)°f(i,j) \qquad (1)$$

g(i,j) is the output image after performing filtering action with the input image and ° is the symbol used for convolution here [16,17].

In this paper, we have used different types of filters like Median filter, Gaussian filter, Wiener filter, Kalman filter and Gabor filter for extracting both ridges and valleys separately from the same blurred fingerprint images.

### *B. Median filter*

A median filter is a non-linear digital filter which is able to preserve sharp signal changes and is very effective in removing impulse noise (or salt and pepper noise) [18]. An impulse noise has a gray level with higher or lower value that is different from the neighborhood point. Linear filters have no ability to remove this type of noise without affecting the distinguishing characteristics of the signal. Median filters have remarkable advantages over linear filters for this particular type of noise. Therefore median filter is very widely used in digital signal and image/video processing applications. When median filters are applied to an image, the pixel values which are very different from their neighboring pixels will be eliminated. By eliminating the effect of such odd pixels, the values are assigned to the pixels that are representative of the values of the typical neighboring pixel in the original image [18, 19].

For any probability distribution on the real line with cumulative distribution function F, regardless of whether it is any kind of continuous probability distribution, in particular an absolutely continuous distribution (and therefore has a probability density function), or a discrete probability distribution, a median m satisfies the inequalities

$$P(X\le m)\ge 1/2 \text{ and } P(X\ge m)\ge 1/2 \qquad (2)$$

in which a Lebesgue – Stieltjes integral is used. For an absolutely continuous probability distribution with probability density function *ƒ*, we have

$$P(X\le m) = P(X\ge m) =\int f(x)dx\ (-\infty,m) = ½ \qquad (3)$$

### *C. Gaussian Filter*

Gaussian filters are a class of linear smoothing filters with the weights chosen according to the shape of a Gaussian function. The Gaussian kernel is widely used for smoothing purpose. The equation of Gaussian filter in one dimension is given by

$$G(x)=(1/\sqrt{(2\pi\sigma^2)})e\wedge(-x^2/2\sigma^2) \qquad (4)$$

In two dimensions, it is the product of two such Gaussians, one in each dimension

$$G(x,y)=(1/(2\pi\sigma^2))e\wedge(-(x^2+y^2)/2\sigma^2) \qquad (5)$$

Where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution.

When applied in two dimensions, this formula produces a surface whose contours are concentric circles with a Gaussian distribution from the center point. Values from this distribution are used to build a convolution matrix which is applied to the original image. Each pixel's new value is set to a weighted average of that pixel's neighborhood. The original pixel's value receives the heaviest weight (having the highest Gaussian value) and neighboring pixels receive smaller weights as their distance to the original pixel increases. This results in a blur that preserves boundaries and edges better than other, more uniform blurring filters.

The Gaussian smoothing filter is a very good filter for removing noise drawn from a normal distribution. Gaussian smoothing is a particular class of averaging, in which the kernel is a 2D Gaussian. Gaussian functions have the following properties that make them useful in image processing, they are (i) Gaussian functions are rotationally symmetric in two dimensions so it will not bias subsequent edge detection in any particular direction. (ii) The Fourier transform of a Gaussian function is itself a Gaussian function. (iii) The degree of smoothening is governed by variance σ. A larger variance σ implies a wider Gaussian filter and greater smoothening. (iv) Two-dimensional Gaussian functions are separable. This property implies that large Gaussian filters can be implemented very efficiently [19].

*D. Wiener Filter*

Wiener filter is used to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. The Wiener-Kolmogorov was the first statistically designed filter to be proposed and subsequently gave rise to many others including the famous Kalman filter. A Wiener filter is not an adaptive filter because the theory behind this filter assumes that the inputs are stationary. Suppose a vector S is corrupted by Gaussian white noise with variance σ2 and mean 0, X = S + σZ. Wiener filtering is the following linear procedure,

$$X\hat{} = \Sigma m(\beta m2/ \beta m2+\sigma 2)[X,gm]gm \qquad (6)$$

Here βm and gm are Eigen values and eigenvectors of the covariance matrix (Karhuen-Loeve transform) of S. If S is Gaussian then X^ is the best mean square estimate of S. In order to apply Wiener filter one needs to estimate the covariance matrix (Karhuen-Loeve transform) of the signal [20].

*E. Kalman Filter*

The main purpose of Kalman filter is to use measurements observed over time, containing noise (random variations) and other inaccuracies, and produce values that tend to be closer to the true values of the measurements and their associated calculated values. The Kalman filter has many applications in technology, and is an essential part of space and military technology development.

In order to use the Kalman filter to estimate the internal state of a process given only a sequence of noisy observations, one must model the process in accordance with the framework of the Kalman filter. This means specifying the following matrices: Fk, the state-transition model; Hk, the observation model; Qk, the covariance of the process noise; Rk, the covariance of the observation noise; and sometimes Bk, the control-input model, for each time-step, k, as described below.

The Kalman filter model assumes the true state at time k is evolved from the state at (k − 1) according to

$$X_k = F_k X_{k-1} + B_k u_k + w_k \qquad (7)$$

Where

- $F_k$ is the state transition model which is applied to the previous state $x_{k-1}$;
- $B_k$ is the control-input model which is applied to the control vector $u_k$;
- $w_k$ is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance $Q_k$.

$$W_k \sim N(0,Q_k) \qquad (8)$$

At time $k$ an observation (or measurement) $z_k$ of the true state $x_k$ is made according to

$$Z_k = H_k x_k + v_k \qquad (9)$$

where $H_k$ is the observation model which maps the true state space into the observed space and $v_k$ is the observation noise which is assumed to be zero mean Gaussian white noise with covariance $R_k$.

$$V_k \sim N(0,R_k) \qquad (10)$$

The initial state, and the noise vectors at each step {x0, w1, ..., wk, v1 ... vk} are all assumed to be mutually independent.

Many real dynamical systems do not exactly fit this model. In fact, unmodelled dynamics can seriously degrade the filter performance, even when it was supposed to work with unknown stochastic signals as inputs. The reason for this is that the effect of unmodelled dynamics depends on the input, and, therefore, can bring the estimation algorithm to instability (it diverges). On the other hand, independent white noise signals will not make the algorithm diverge. The problem of separating between measurement noise and unmodelled dynamics is a difficult one and is treated in control theory under the framework of robust control [21].

*F. Gabor filter*

In image processing, a Gabor filter, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation. Thus, image analysis by the Gabor functions is similar to perception in the human visual system.

Its impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually.

Complex

$$G(x,y;\lambda,\theta,\Psi,\sigma,\gamma) = \exp\left(-(x'^2+\gamma^2 y'^2)/2\sigma^2\right) \exp(i(2\pi(x'/\lambda)+\Psi)) \qquad (11)$$

Real

$$G(x,y;\lambda,\theta,\Psi,\sigma,\gamma) = \exp\left(-(x'^2+\gamma^2 y'^2)/2\sigma^2\right) \cos(2\pi(x'/\lambda)+\Psi) \qquad (12)$$

Imaginary

$$G(x,y;\lambda,\theta,\Psi,\sigma,\gamma) = \exp\left(-(x'^2+\gamma^2 y'^2)/2\sigma^2\right) \sin(2\pi(x'/\lambda)+\Psi) \qquad (13)$$

Where $x' = x \cos\theta + y \sin\theta$ (14)

And $y' = -x \sin\theta + y \cos\theta$ (15)

In this equation, $\lambda$ represents the wavelength of the sinusoidal factor, $\theta$ represents the orientation of the normal to the parallel stripes of a Gabor function, $\psi$ is the phase offset, $\sigma$ is the sigma of the Gaussian envelope and $\gamma$ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function [8].

## III. POST PROCESSING

After preprocessing on the binary and skeleton images, we extract all the minutiae from the fingerprint skeleton using any one of the above mentioned filters. However, due to various noises in the fingerprint image, the extraction algorithm produces a large number of spurious minutiae such as break, spur, bridge, merge, triangle, ladder, lake, island, and wrinkle. Therefore, reliably differentiating spurious minutiae from genuine minutiae in the Post processing stage is crucial for accurate fingerprint recognition. The more spurious minutiae are eliminated, the better the matching performance will be. In addition, matching time will be significantly reduced because of the reduced minutiae number. This is very important since the execution time is a critical parameter in an AFIS.

After the false minutiae are removed, the original extracted features from the image is alone stored in the database. While storing the features, the respective identity of the person ((i.e.) name, number etc) is allotted for each image for further identification [22].

## IV. MATCHING

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 offline process the verification time still depends on the time taken to generate a single template [23].

## V. CONCLUSION AND FUTURE WORK

### *A. Conclusion*

From this work, we have analyzed the following points, When compared to ridges in blurred fingerprint image, more number of valleys can be extracted. So if blurred fingerprint images are obtained we can go extracting valleys instead of ridges, because in some blurred fingerprints not even a single ridge can be extracted. But we observed in this work that 3 to 4 valleys are obtained in the same fingerprint image. All filters have extracted more number of valleys than ridges in this work. But time elapsed for ridge extraction is less when compared to valley extraction. But this disadvantage can be neglected in the case of blurred fingerprint images and also enhancement of images is not required in this work.

Future *Work*

In our future work, we are going to modify all the above mentioned filters to check the above results.

Also, we are trying to reduce the time elapsed for valley extraction, because in Automatic Fingerprint

Identification System (AFIS) time reduction is a very important factor.

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