

ADAPTIVE FINGERPRINT IMAGE ENHANCEMENT USING HISTOGRAM EQUALIZATION

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Abstract— This article adaptively improves the fingerprint image quality and enhances it. The term adaptive means that the measuring factors of the method are automatically adjusted based on the input fingerprint image. It is a faster means to enhance the fingerprint image for many purposes like matching, orientation estimation etc. Mainly four step comprise this method, in which different forms of order statistical filters are applied and a nonlinear dynamic range adjustment method is also used.

Index Terms—orientation, valley, ridges.

I. INTRODUCTION

UNTIL many centuries, fingerprint matching was used only for forensic purposes and experts performed the fingerprint analysis manually. Research has been conducted the last 50 years to develop automatic fingerprint identification systems (AFIS). However, fingerprint matching, especially when the fingerprint images have low quality or when the matching is performed in altered fingerprint, is still an open research question. The main problem in automatic fingerprint identification is to acquire matching reliable features from fingerprint images with poor quality.

There are many filtering methods available, in which Contextual filtering is a popular technique for fingerprint enhancement, where filter features are aligned with the local orientation and frequency of the ridges in the fingerprint image. The first method utilizing contextual filters to enhance fingerprint images performed both the filter design and the filtering in the spatial domain. The method used a main filter having a horizontally directed pattern designed based on four manually identified parameters for each fingerprint image.

Another fingerprint enhancement methods employ directional Gabor or Butterworth bandpass filters where the filtering is performed in the frequency domain. A method based on curved Gabor filters that locally adapts the filter shape to the curvature and direction of the flow of the fingerprint ridges is introduced. This new type of Gabor filter

design, shows a potential in fingerprint image enhancement in comparison to classical Gabor filter methods.

But the computational load is high which inhibits its use in practical application.

Another method that differs from the classical directional filter design approaches is that instead of constant parameters for each fingerprint image, the magnitude spectrum of each local area of the fingerprint image was used directly to filter the same local area in the frequency domain. The idea behind this method is that alike matched filter the local magnitude spectrum carries similar properties, and by using magnitude spectrum directly as a filter, components that are dominant related to ridges are amplified. However it less useful in practical situations because it is noted that this approach provides noise gain.

Method described above keep various parameters constant, such as local area size. In a real application the strategy to keep parameters constant may fail where fingerprint image or sensor characteristics vary, thus yielding varying image quality. In addition, due to the variable nature of fingerprints spatially, it is crucial to have a sufficient amount of data in each local image area so that the local structure of the fingerprint is enclosed. Hence, the local area size should adapt to the data. Different fingerprint sensor resolutions provide different spatial frequencies of the same fingerprint and this also requires adaptive parameters. Depending on, e.g., gender and age of the user, fingerprints captured with the same sensor may also vary.

These paper mainly consist of four steps ie a)preprocessing b)global analysis c)local adaptive analysis and d)matched filtering. In preprocessing a nonlinear dynamic range adjustment method is used. Successive Mean Quantization Transform (SMQT) is one of such methods in which many levels of quantization is used and number of levels is equal to the number of bits used to represent the SMQT processed image. The SMQT can be viewed as a binary tree build of a simple Mean Quantization Units (MQU) where each level performs an automated break down of the information. Hence, with increasing number of levels the more detailed underlying information in the image is revealed. SMQT uses eight level of quantization. Since it is recursive process, it takes much time to compute.

Hence in this method histogram equalization is been used in the pre-processing stage hence quality is increased.



Fig 1:Fingerprint sensor images of the (a) little finger of a 30-year-old man, and the (b) little finger of a 5-year-old boy, illustrate the varying fingerprint image quality.

II. PROPOSED METHOD

It is based on the basic principle that when a spatial sinusoidal signal and its corresponding magnitude spectrum is taken together with a local fingerprint image patch then following were observed:

- 1) Local fingerprint image patches are spectrally and spatially similar to a sinusoidal signal, where the dominant peaks in magnitude spectrums of the two signals are co-located.
- 2) The dominant peak in the magnitude spectrum of a local image area carries information about the local orientation and frequency of the fingerprint pattern.
- 3) The quality of the fingerprint is determined from the magnitude of the dominant spectral peak acts as of that particular local area.

These observations are necessary to design matched directional filters. A segmentation are then performed in the spatial domain based on the extracted local features.

A. PREPROCESSING

Histogram equalization is used in preprocessing stage as its fast and gives out a good contrast of the image. It is a powerful point processing enhancement technique that seeks to optimize the contrast of an image at all points. As the name suggests, histogram equalization seeks to improve image contrast by equalizing or flattening, the histogram of an image. The input image is transformed $T(.)$ such that the gray values in the output is uniformly distributed in $[0, 1]$. Let

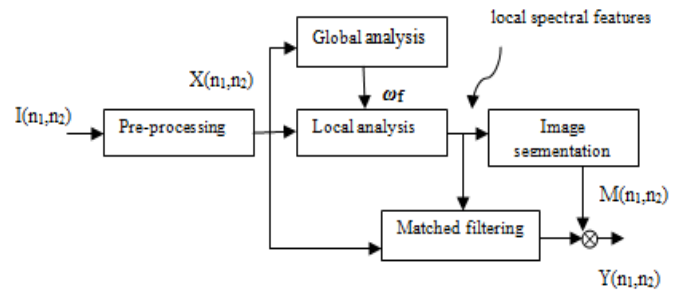


Fig 2:Initial blocks of enhancement

us assume that the input image to be enhanced has continuous gray values, with $r = 0$ representing black and $r = 1$ representing white.

Hence a gray value transformation is designed $s = T(r)$, based on the histogram of the input image, which will enhance the image.

As before, we assume that:

- (1) $T(r)$ is a increasing function monotonically for $0 < r < 1$ (preserves order from black to white).
- (2) $T(r)$ maps $[0,1]$ into $[0,1]$ (preserves the range of allowed Gray values).

Let denote the inverse transformation by $r = T^{-1}(s)$ by assuming that the inverse transformation also satisfies the above two conditions.

The gray values in the input image and output image are considered as the random variables in the interval $[0, 1]$. Let $p_{in}(r)$ and $p_{out}(s)$ denote the probability density of the Gray values in the input and output images.

If $T(r)$ and $p_{in}(r)$ are known, and $r = T^{-1}(s)$ satisfies condition 1, then

$$p_{out}(s) = \left[p_{in}(r) \frac{dr}{ds} \right]_{r=T^{-1}(s)} \quad (1)$$

Hence, one way to enhance the image is to design a transformation $T(.)$ and that the gray values in the output is distributed uniformly in $[0, 1]$, i.e. $p_{out}(s) = 1$, $0 < s < 1$. In terms the output image will have all gray values in “equal proportion”. This technique is called histogram equalization.

Histogram equalization defines a mapping of levels p into levels q such that the distribution of gray level q is uniform. This mapping expands the range of gray levels (stretches contrast) for gray levels near to histogram maxima. When this contrast is expanded for most of the image pixels, thus it improves the detect ability of many image features. The PDF of a pixel intensity level r_k is given by:

$$P_r(r_k) = n_k/n \quad (2)$$

B. GLOBAL ANALYSIS

Global analysis is performed in order to find out the fundamental frequency of the input equalized image.

The magnitude spectrum of a fingerprint image typically contains a circular structure around the origin. The circular structure stems from the fact that a fingerprint has nearly the same spatial frequency throughout the image but varying local orientation. The circular structure in the magnitude spectrum has been used for estimating fingerprint quality. In a recent study, the circular spectral structure was exploited to detect the presence of a fingerprint pattern in the image. This paper employs that the radially dominant component in the circular structure corresponds to the fundamental frequency of the fingerprint image. This fundamental frequency is inversely proportional to a fundamental window size which is used as a base window size in our method.

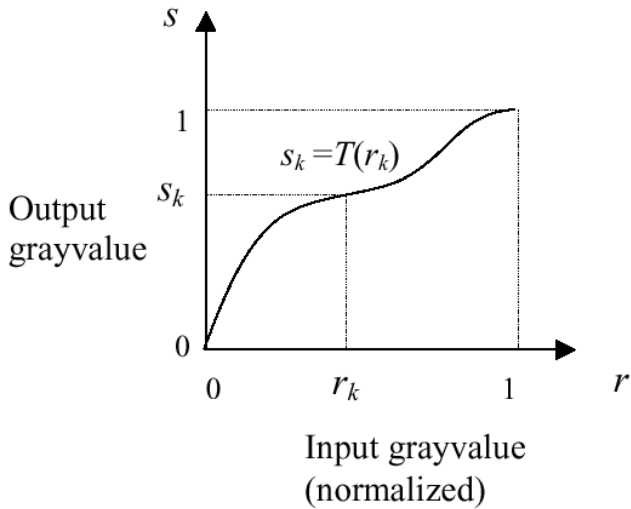


Fig 3:O/P grayvalue vs I/P grayvalue

Where $k=0,1,\dots,255$, n is the total number of pixels and n_k is the number of pixels at intensity level r_k . The histogram is derived by plotting $p_r(r_k)$ against r_k .

Hence, new intensity s_k is defined as:

$$s_k = \frac{\sum_{j=1}^N n_j}{n} \quad (3)$$

I have apply the histogram equalization locally by using a local windows of 11×11 pixels. This results in expanding the contrast locally, and changing the intensity of each pixel according to its local neighborhood presents the improvement in the image contrast obtained by applying the local histogram equalization.



Fig4: original image (left) and after histogram equalization (right)

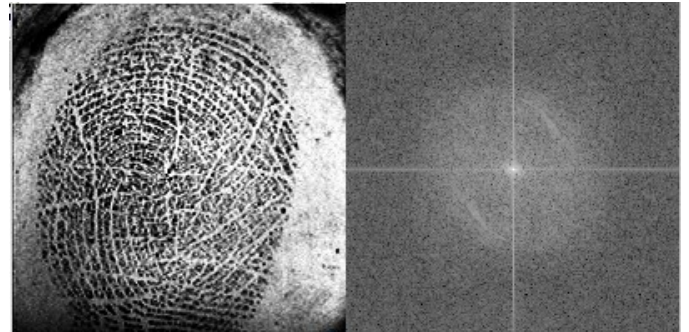


Fig 5 Fingerprint image and (b) corresponding magnitude spectrum

The circular structure around the origin in the fingerprint magnitude spectrum stems from the characteristics of the periodic fingerprint pattern.

The fundamental fingerprint frequency is estimated according to the following steps:

- 1) A median filter is used in the new processing stage that suppresses data outliers.
- 2) From the median filtered image a radial frequency histogram is computed.
- 3) The fundamental frequency is assumed located at the point where the radial frequency histogram attains its maximal value. The smoothing of radial frequency histogram is herein proposed to reduce the impact of spurious noise.

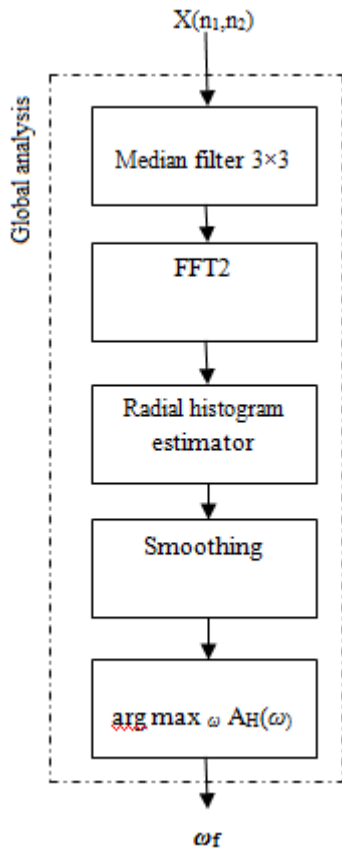


Fig 6: Processing blocks of the global analysis

1) *Step 1 - Data-Outlier Suppression:* A 3×3 median filter is applied to the histogram equalized image in order to suppress data outliers. The median filtered fingerprint image is denoted as $Z(n1, n2) = \text{Median}_{3 \times 3} \{X(n1, n2)\}$.

2) *Step 2 - Radial Frequency Histogram:* Let the two-dimensional Fourier transform of the pre-processed image is denoted as $F(\omega_1, \omega_2) = F\{Z(n1, n2)\}$ and median filtered input image $Z(n1, n2)$, where, $\omega_1 \in [-\pi, \pi]$ and $\omega_2 \in [-\pi, \pi]$ denote normalized frequency. Fourier domain filtering and pre-filtered images used permits us to convolve the fingerprint image with filters of full image size, since the two-dimensional FFT algorithm can be used to calculate convolutions efficiently. In this way our directional filtering is performed using information from the entire image rather than from a small neighbourhood, and this leads to more effective noise reduction in the filtered image. Two-dimensional FFTs are computationally efficient and are standard on all modern image processing systems.

The enhancement consists of a filtering stage and then a thresholding stage. This filtering stage produces a directionally smoothed version of the image from which most of the unwanted information (‘noise’) has been removed, but which still contains the desired information (i.e. the ridge structure and minutiae). Next the thresholding stage produces the binary, enhanced image. For clarity in the presentation the

spectral image is represented in polar form, i.e., $F(\omega_1, \omega_2) \equiv F(\omega, \theta)$, related through the following change of variables $\omega_1 = \omega \cdot \cos \theta$ and $\omega_2 = \omega \cdot \sin \theta$, where ω is the normalized radial frequency and θ denotes the polar angle.

By integrating the magnitude spectrum $|F(\omega, \theta)|$ along the polar angle θ , a radial frequency histogram $A(\omega)$ can be obtained according to

$$A(\omega) = \frac{1}{2\pi} \int_0^{2\pi} |F(\omega, \theta)| d\theta$$

$$= \frac{1}{\pi} \int_0^\pi |F(\omega, \theta)| d\theta \quad (4)$$

where, due to the complex conjugate symmetry of $F(\omega, \theta)$, it is sufficient to integrate only over one half-plane in

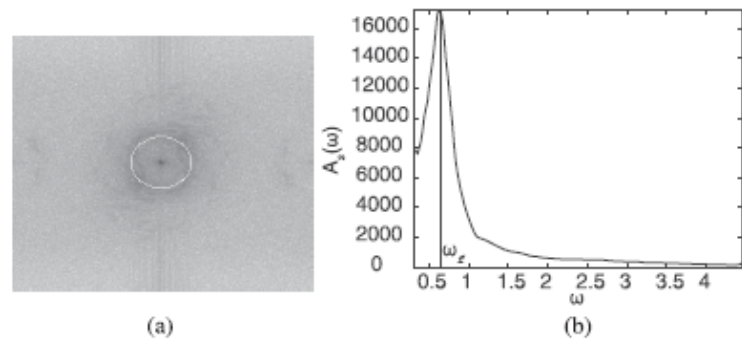


Fig 7: Fingerprint magnitude spectrum with an overlaid circle whose radius corresponds to the (a) estimated fundamental frequency ω_f and the corresponding radial-frequency histogram $A_s(\omega)$ whose peak value is located at (b) the fundamental frequency.

3) *Step 3 - Fundamental Frequency Estimation:* Due to noisy input signals the radial frequency histogram may contain impulsive noise. This paper therefore proposes a smoothing filter (smoothing along the ω -variable in $A(\omega)$) to suppress the impulsive noise, where $A_s(\omega)$ is the smoothed radial frequency histogram. The radial frequency at the point where the radial frequency histogram attains its largest value corresponds to the fundamental frequency ω_f of the fingerprint image

$$\omega_f = \arg \max_{\omega} A_s(\omega)$$

$$\omega \in [\omega_{\min}, \pi] \quad (6)$$

The lower boundary ω_{\min} is also introduced in order to avoid erroneous peak values related to low frequency noise. Hence, the lower search boundary is computed as

$$\omega_{\min} = 2. \pi. 10 / \max(N_1, N_2) \quad (7)$$

The radial frequency is made discrete in the implementation for practical reasons, and a five point FIR filter with the Z-transform $H(z) = 15(1 + z^{-1} + z^{-2} + z^{-3} + z^{-4})$ is used to smooth the radial frequency histogram. An example of a fingerprint magnitude spectrum together with a corresponding radial frequency histogram is illustrated in Fig. 7.

The fundamental frequency ω_f , computed is inversely proportional to a fundamental area size L_f , according to

$$L_f = \frac{2\pi}{\omega_f} \quad (8)$$

The major advantage of the method proposed in this paper is that it is adaptive towards sensor and fingerprint variability. The adaptive behaviour is due to that the estimated fundamental area size acts as a base window size in all stages of the method. Hence, no parameter tuning is required to use the proposed method for different sensors or applications.

C. LOCAL ADAPTIVE ANALYSIS

Adaptively estimating local spectral features corresponding to fingerprint ridge frequency and orientation is the purpose of the local analysis. Most parts of a fingerprint image on a local scale have similarities to a sinusoidal signal in noise. Hence, they have a magnitude spectrum oriented in alignment with the spatial signal and with two distinct spectral peaks located at the signal's dominant spatial frequency

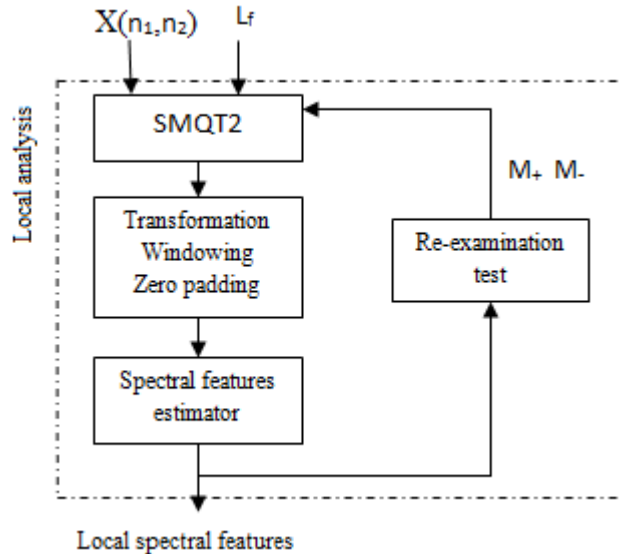


Fig 8: Processing blocks of the local adaptive analysis

In addition, the magnitude of the dominant spectral peak in relation to surrounding spectral peaks indicates the strength of the dominant signal. These features are utilized in the local analysis.

The fundamental area size L_f computed in Eq. 8 is used as a fundament in the local analysis. The size of the local area in the local analysis is $M \times M$, where M is an odd-valued integer computed as

$$M = 2 \lceil kL_f/2 + 1 \rceil - 1 \quad (9)$$

number of fundamental periods enclosed by each local area is controlled by parameter k , which is a design parameter.

Two additional local area sizes are introduced due to the local variability of a fingerprint, in regions around cores, deltas and minutiae where the fingerprint ridges are curved or when the local ridge frequency deviates from the estimated fundamental frequency ω_f . A larger local area size, denoted as $M+ \times M+$, where $M+ = (1 + \eta) \cdot M$, and a smaller local area size, denoted as $M- \times M-$, where $M- = (1 - \eta) \cdot M$, are considered here. Note that both $M+$ and $M-$ are forced to be odd-valued integers. The design parameter $\eta \in [0, 1]$ defines the change, i.e., growth and shrinkage, of the larger and smaller area sizes in relation to the nominal local area size.



Fig 9: Example of local area size $M \times M$, and corresponding sizes after growth $M+ \times M+$ and shrinkage $M- \times M-$.

It is stressed that all parameters used herein are functions of the automatically estimated fundamental area size L_f . Hence, the size of the local area, including the larger and smaller area sizes, automatically adapt to fingerprint and sensor variability. The approach to use three different sizes of the local area. Similar methods that incorporate multi-size windows or fingerprint image scaling are proposed. However, these methods adapt on a global scale, and this stands in contrast to the proposed method that adapts to each fingerprint on a local scale and thereby matches local variability better. Each local area is centered around the point (n_1, n_2) in the pre-processed image $X(n_1, n_2)$ according to

$$J_{n_1, n_2}(m_1, m_2) = X(n_1 + m_1, n_2 + m_2)$$

Where $m_1 = (-M-1)/2 \dots (M-1)/2$ and $m_2 = (-M-1)/2 \dots (M-1)/2$ coordinates in the local area. To clarify the presentation in the sequel, the notation of a local area, a local variable, or a local parameter is done without the local area sub-index n_1, n_2 i.e. $J_{n_1, n_2}(m_1, m_2) \equiv J(m_1, m_2)$.

In the local analysis the following steps are carried out for each local area:

- 1) A local dynamic range adjustment is proposed to be applied to each local area

2) A data-driven transformation is conducted in order to improve local spectral features estimation. The data for each local area were windowed and zero padded to the next larger power of two .

3) Local magnitude spectrum is computed and the dominant spectral peak is located from which the orientation local features frequency, and magnitude are estimated.

4) A test is done if the local area needs to be reexamined, using a larger and a smaller size of the local area, is conducted. Repeating steps 1–3 of the local analysis using these alternative area sizes if a reexamination is required.

1) Step 1 -Dynamic Range Adjustment:

Low quality fingerprint images consist of regions with a poor contrast between signal (i.e., fingerprint pattern), and background usually. Even after global contrast enhancement this poor contrast may remain in some local areas .Local image areas having this poor contrast yield very unsatisfactory local features extraction due to low signal to noise ratio. The SMQT dynamic range adjustment method is applied as the local contrast enhancement on each local image area according to $H(m1,m2) = SMQT2 \{J(m1,m2)\}$. Thus it is noted that, the local analysis is based on local areas $J(m1,m2)$ of the globally SMQT-processed $X(n1, n2)$ image.

Through empirical analysis, it has been found that the SMQT used for local dynamic range adjustment only requires a two-bit representation, i.e., $B = 2$, without degrading the local spectral features estimation.

2) Step 2 - Data Transformation, Windowing, Zero Padding:

A spatial window is been used in the local analysis to suppress spectral side-lobes. When a fingerprint valley if appear in the centre of the local area the use of this window may yield feature estimation errors since the window suppresses adjacent ridges. Hence, the dominant peak will be suppressed in the frequency spectrum as well.

A simple test triggers data-transformation that circumvents this problem. Arithmetic mean, denoted as \bar{H} , is estimated for values of data in and around the centre of each local area according to

$$\bar{H} = \frac{1}{(2K+1)^2} \sum_{k1=-K}^K \sum_{k2=-K}^K H(k1, k2) \tag{10}$$

Where the parameter $K = [(M - 1)/4]$ controls the number of center points included in the estimate. The test and the following data transformation

$$\text{If } \bar{H} > 2^{B-1} \cdot H(m1,m2) \leftarrow 2^{B-1} \cdot H(m1,m2) \tag{11}$$

where $2B - 1$ denotes the maximal signal value for an image having B bits of dynamic range, where $B = 2$ due to the two-

bit SMQT representation. The proposed test and transformation imply that, the sample values in the local area are inverted if the mean value is above half of the maximal dynamic range, which corresponds to having a fingerprint valley in the centre of the local image area.

To improve local features extraction, the frequency spectrum has to have an adequate resolution. Therefore, every transformed local area is zero padded to next higher power of two since an FFT is used to frequency-transform the image. A two dimensional Hamming window is applied to the local area in order to reduce the magnitude of spectral side-lobes, thus smoothing the transition between data and the zero-padding. These steps are thus carried out for each local area, but where the local area indices $n1$ and $n2$ are omitted for clarity in the presentation.

3) Step 3 - Spectral Features Estimation:

A local magnitude spectrum $G(\omega_1, \omega_2) = |F \{H(m1,m2)\}|$ is obtained by computing the modulus of the two-dimensional Fourier transform of the transformed, zero-padded and windowed local area $H(m1,m2)$. Spectral features include the magnitude PD and frequencies $\omega_{D,1}, \omega_{D,2}$ of the dominant spectral peak and the magnitude of the second largest spectral peak PD_2 .

A quality measure is computed based on the extracted features. The measure PD/P_{max} quantifies the significance of the largest peak in relation to P_{max} , the maximum magnitude possible including the bias of the window. The measure PD_2/PD assesses the relationship between the two largest spectral peaks, PD and PD_2 , found in the magnitude spectrum of each local area. If the local area contains a dominant narrowband signal, such as a fingerprint pattern, PD/P_{max} will be close to unity and PD_2/PD will be close to zero. Hence, the measure

$$Q = PD/P_{max} + (1 - PD_2/PD) \tag{12}$$

reflects the overall quality of the local area by combining these two measures. The measure Q is thus referred to as a quality map where $Q = 2$ implies best quality and $Q = 0$ worst quality.

It is noted that each local area comprises a set of features, hence, the entire fingerprint image is represented, after the local analysis, by the feature maps $PD(n1, n2), \omega_{D,1}(n1, n2), \omega_{D,2}(n1, n2), PD_2(n1, n2)$, and $Q(n1, n2)$.

4) Step 4 - Local Area Re-examination Test:

Some local areas need to be analyzed using a different local area size than the fundamental area size due to the variability in some regions of a fingerprint. Regions where the fingerprint ridges are curved, such as near cores, deltas and minutiae points, or where the local ridge frequency deviate from the estimated fundamental frequency ωf , may yield inaccurate spectral features estimates. These regions are re-examined using two additional sizes of the local area. A re-examination of the local area is conducted if $Q \leq Q_T$, where Q_T is a system

design threshold. This means that steps 1-3 of the local adaptive analysis are repeated using the larger and smaller area sizes M^+ and M^- , respectively. After the re-examination using the two new local area sizes is completed, similar quality scores Q^+ and Q^- are calculated from the features from each respective stage. The final spectral features are chosen based on which of the measures Q , Q^+ and Q^- have the best quality (i.e., highest value).

III. MATCHED FILTERING

A local area that contains a fingerprint image pattern renders a strong dominant peak since it is highly periodic in nature. The estimated local features $\omega_{D,1}$ and $\omega_{D,2}$ represent, respectively the vertical and horizontal spatial frequencies of the local dominant spectral peak.

These estimated frequencies $\omega_{D,1}$, $\omega_{D,2}$ are highly varying, e.g., where local curvature or irregularities such as cores, deltas and minutiae points in the fingerprint are located. A smoothing of these frequencies is thus performed to reduce the impact of this noise. This smoothing is conducted on the polar coordinates $\omega_D \equiv \omega_D(n1, n2)$ and $\theta_D \equiv \theta_D(n1, n2)$ instead of the Cartesian coordinates $\omega_{D,1}$ and $\omega_{D,2}$ related as

$$\omega_D = \sqrt{\omega_{D1}^2 + \omega_{D2}^2} \quad (13)$$

$$\theta_D = \arctan(\omega_{D,2}/\omega_{D,1})$$

The smoothing is performed by filtering ω_D and θ_D using order statistical filters, so called α trimmed mean filter, along the $n1, n2$ -dimensions. The α -trimmed mean filter uses an observation window, of size $2L+1 \times 2L+1$ where $L = [\gamma \cdot Lf]$ and γ is a design parameter. The sample values within the observation window are sorted and arranged into a column-vector containing $(2L+1)^2$ values. The output value of the filter is the mean of the $(1-\alpha) \cdot (2L+1)^2$ central sample values in the sorted vector, i.e., $\alpha \cdot (2L+1)^2$ extreme values at the beginning and at the rear of the sorted vector are excluded from the mean. The parameter α is a design parameter. It is stressed that all parameters used herein are functions of the automatically estimated fundamental area size Lf . Hence, the size and shape of the order statistical filter, automatically adapt to fingerprint and sensor variability. The polar angle map, θ_D is phase-wrapped around the values 0 and π before smoothing by the order statistical filter to avoid irregular results, and the phase is reconstructed after the filtering. The smoothed polar coordinates are denoted as $\tilde{\omega}_D$ and $\tilde{\theta}_D$, respectively, and the corresponding smoothed Cartesian frequencies are thus $\tilde{\omega}_{D,1} = \tilde{\omega}_D \cdot \cos \tilde{\theta}_D$ and $\tilde{\omega}_{D,2} = \tilde{\omega}_D \cdot \sin \tilde{\theta}_D$.

The smoothed spatial frequencies are used to construct a filter $f(m1, m2)$, where $(m1, m2) \in [-N, N]$, matched to the local area at hand. The size of the filter is selected as $2N+1 \times 2N+1$, where

$$N = \text{round} \left\{ \frac{\pi}{\max(|\tilde{\omega}_{D,1}|, |\tilde{\omega}_{D,2}|)} \right\} \quad (14)$$

i.e., rounded to the nearest integer value.

The filter comprises a basis function $\phi(m1, m2)$ tapered with a spatially orthogonal tapering function $\tau(m1, m2)$, according to

$$f(m1, m2) = \phi(m1, m2) \cdot \tau(m1, m2), \quad (13)$$

The basis function is a cosine function aligned to the frequency and orientation of the dominant peak, i.e.,

$$\Phi(m1, m2) = \cos(\tilde{\omega}_{D,1} \cdot m1 + \tilde{\omega}_{D,2} \cdot m2) \quad (16)$$

and the tapering function is orthogonal thereto

$$\tau(m1, m2) = \cos(c \cdot (\tilde{\omega}_{D,1} \cdot m1 + \tilde{\omega}_{D,2} \cdot m2)) \quad (17)$$

C is a scalar variable used to stretch the tapering function so that it has the value 0.25 where the basis function intersects the filter boundary, C . The enhanced output image value at the point $(n1, n2)$ is the local area weighted by the corresponding matched filter.

$$Y(n1, n2) = \sum_{m1=-N}^N \sum_{m2=-N}^N f(n1, n2)(k1, k2) \cdot X(n1+m1, n2+m2) \quad (18)$$

IV. IMAGE SEGMENTATION

Image segmentation is the process of subdividing an image into its constituent part or objects in an image. A captured fingerprint image usually consists of two components that are called the foreground and the *background*. Here, background is the noisy area at the borders of the image. The component that originated from the contact of a fingertip with the sensor is called as foreground. Some algorithms of segmentation also define some part of the foreground as *low quality area*. The segmentation algorithm is described in [13], the task of the fingerprint segmentation algorithm is to decide which part of the image belongs to the background, which part to the foreground, and which part is a low quality area.

This renders that fingerprint patterns obtained by a fingerprint scanner with a large sensor area only occupy a part of the image, as opposed to a scanner with a small sensor area. To suppress non-relevant parts of a fingerprint image, where there is no fingerprint data, this process of segmentation of image is performed. In this paper, the segmentation of the fingerprint image is performed by applying a binary mask to the fingerprint image and is identical to where the estimated spectral features from the local analysis are used to construct the binary mask. An additional post processing step is used to remove falsely segmented structured background from the binary mask. The output image is the element-wise product of the binary mask and the matched filter output signal, i.e., $Y(n1, n2)$.

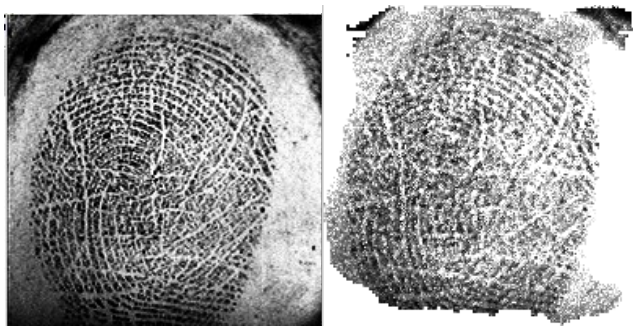


Fig 9:Original image (left)and segmented image(right)

Table 1: values of the design parameters chosen in this paper

Parameter	Value
K	3
H	0.3
A	0.6
Γ	0.5
Q_T	1

V. Conclusion

This paper presents an adaptive fingerprint enhancement method that is fast and efficient. Processing of data is done on both global and local level. A pre-processing using histogram equalization adjustment method is used to enhance the global contrast of the fingerprint image prior to further processing. Estimation of the fundamental frequency of the fingerprint image is improved in the global analysis by utilizing a median filter leading to a robust estimation of the local area size. An implementation of median filter is done to suppress the noise and data outliers. A low-order SMQT dynamic range adjustment is conducted locally in order to achieve reliable features extraction used in the matched filter design and in the image segmentation. The matched filter block is improved by applying order statistical filtering to the extracted features, thus reducing spurious outliers in the feature data. The ability of the proposed method to adapt to various fingerprint image ranges from 5 to 73 years

References

[1] Adaptive Fingerprint Image Enhancement With Emphasis on Preprocessing of Data Josef Ström Bartoňek, Student Member, IEEE, Mikael Nilsson, Member, IEEE, Benny Sällberg, Member, IEEE, and Ingvar Claesson, Member, IEEE

[2] Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*. 2nd ed. New York: Springer-Verlag, 2009..

[3] L. O’Gorman and J. V. Nickerson, “Matched filter design for fingerprint image enhancement,” in *Proc. Int. Conf. Acoust. Speech Signal Process.*, vol. 2. Apr. 1988, pp. 916–919.

[4] B. G. Sherlock, D. M. Monro, and K. Millard, “Fingerprint enhancement by directional Fourier filtering,” *IEE Proc.-Vis., Image Signal Process.*, vol. 141, no. 2, pp. 87–94, Apr. 1994

[5] M. Tico, M. Vehvilainen, and J. Saarinen, “A method of fingerprint image enhancement based on second directional derivatives,” in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process.*, Mar. 2005, pp. 985–988.

[6] C. Gottschlich, “Curved-region-based ridge frequency estimation and curved Gabor filters for fingerprint image enhancement,” *IEEE Trans. Image Process.*, vol. 21, no. 4, pp. 2220–2227, Apr. 2012.

[7] Fingerprint Image Enhancement using Filtering Techniques, Shlomo Greenberg, Mayer Aladjem, Daniel Kogan and Itshak Dimitrov Electrical and Computer Engineering Department, Ben-Gurion University of the Negev, Beer-Sheva,

[8] A. Willis and L. Myers, “A cost-effective fingerprint recognition system for use with low-quality prints and damaged fingertips,” *Pattern Recognit.*, vol. 34, no. 2, pp. 255–270, 2001.

[9] A. Uhl and P. Wild, “Comparing verification performance of kids and adults for fingerprint, palmprint, hand-geometry and digitprint biometrics,” in *Proc. IEEE 3rd Int. Conf. Biometrics, Theory, Appl., Syst.*, Mar. 2009, pp. 1–6.

[10] J. S. Bartoňek, M. Nilsson, J. Nordberg, and I. Claesson, “Adaptive fingerprint binarization by frequency domain analysis,” in *Proc. IEEE 40th Asilomar Conf. Signals, Syst. Comput.*, Oct.–Nov. 2006, pp. 598–602.

[11] B. J. Ström, N. Mikael, N. Jörgen, and C. Ingvar “Improved adaptive fingerprint binarization,” in *Proc. IEEE Congr. Image Signal Process.*, May 2008, pp. 756–760.

[12] H. Fronthaler, K. Kollreider, and J. Bigun, “Local features for enhancement and minutiae extraction in fingerprints,” *IEEE Trans. ImageProcess.*, vol. 17, no. 3, pp. 354–363, Mar. 2008.

[13] Asker M. Bazen, August 19, 2002 Fingerprint Identification - Feature Extraction, Matching, and Database Search

[14] Ishmael S. Msiza, Fingerprint segmentation: an investigation of various techniques and a parameter study of a variance-based method, International Journal of Innovative Computing, September 2011