The novel method for Adaptive Image Enhancement Using Histogram Equalization

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Abstract— *The article adaptively improves the fingerprint image quality, reduces noise 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 steps comprise this method, in which there are two forms based on histogram equalization and other based on order of anisotropic filters are applied and a nonlinear dynamic range adjustment method is also used.*

Keywords— Look Up Table (LUT); anti-symmetric product coding (APC); odd-multiple-storage (OMS; distributed arithmetic (DA);

1. INTRODUCTION

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. Other fingerprint enhancement methods employ directional Gabor or Butterworth band pass 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.

The other filter method is anisotropic filter, which is used to reduce the noise presence in the image on selected area of the image. Anisotropic diffusion resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Each of the resulting images in this family is given as a convolution between the image and a 2D isotropic Gaussian filter, where the width of the filter increases with the parameter. This diffusion process is a linear and space-invariant transformation of the original image.

Anisotropic diffusion is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a non-linear and space-variant transformation of the original image.

The anisotropic 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, illustrates the varying fingerprint image quality.

2.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. Segmentation is then performed in the spatial domain based on the extracted local features.

3. 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 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.

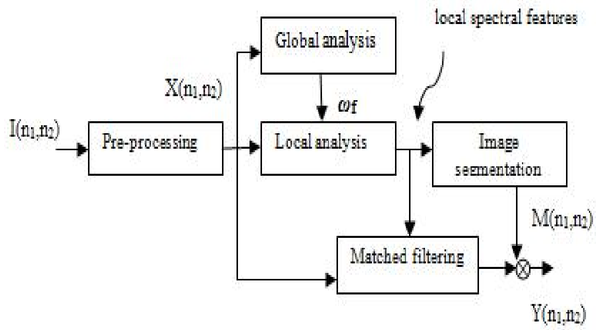

Fig 2: Initial blocks of enhancement

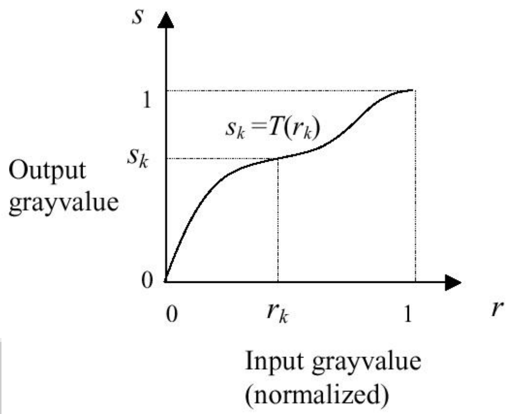

Fig 3: O/P gray value vs. I/P gray value

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 pout(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

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

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. $p_{out}(s) = 1$, $p_{out}(s) = 1, 0 < s < 1$ .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:

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

where k=0,1….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:

$$\sum_{k=1}^{N} nj \quad / n \quad (3)$$

I have apply the histogram equalization locally by using a local windows of 11x11 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)

4. 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 radically 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.

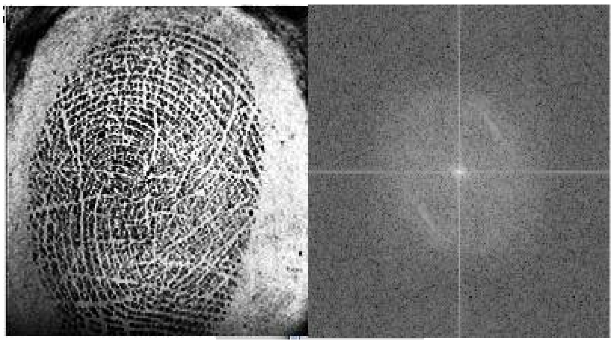

Fig 5 Fingerprint image and (b) corresponding magnitude spectrum

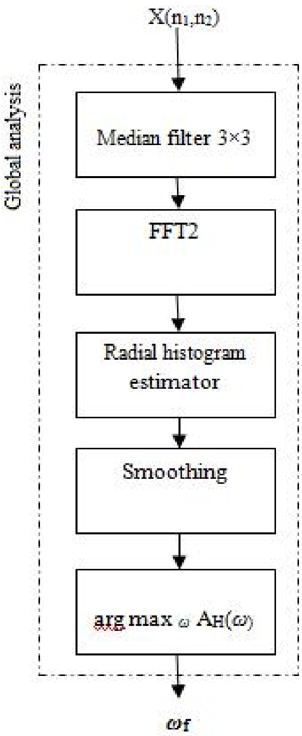

Fig 6: Processing blocks of the global analysis

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 $Z(n1, n2) = \text{Median}3\times3\ \{X(n1, n2)\}$.

2) *Step 2 - Radial Frequency Histogram:* Let the two-dimensional Fourier transform of the pre-processed image is denoted as $F(\omega1, \omega2) = F\{Z(n1, n2)\}$ and median filtered input image $Z(n1, n2)$, where, $\omega1 \in [-\pi, \pi)$ and $\omega2 \in [-\pi, \pi)$ 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 neighborhood, and this leads to more effective.

Two- dimensional FFTs are computationally efficient and are standard on all modern image processing systems. The enhancements consist 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

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

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

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

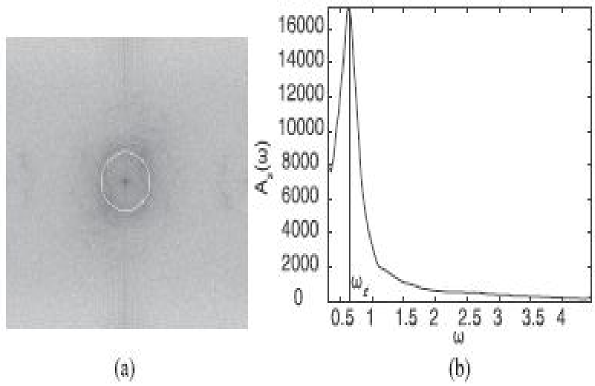

Fig 7: Fingerprint magnitude spectrum with an overplayed circle whose radius corresponds to the (a) estimated fundamental frequency ω f and the corresponding radial-frequency histogram As(ω) whose peak value is located at (b) the fundamental frequency.

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 $AS(\omega)$ 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 $\omega\ f$ of the fingerprint image

$$\omega_f = \arg\max A_s(\omega)$$

$$\omega \in [\ _{min}, \pi] \tag{6}$$

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

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

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

$$L_f = \frac{2\pi}{\omega f} \tag{8}$$

The major advantage of the method proposed in this paper is that it is adaptive towards sensor and fingerprint variability. The adaptive behavior 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.

5. 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.

The smoothing is performed by filtering ωD and θ_D using order diffusion 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 $L = [\gamma \cdot L f$] 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 $L\ f$. 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 $\tilde{\omega}_{D,2} = \tilde{\omega}_D \cdot \sin \tilde{\theta}_D$.

6. 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.

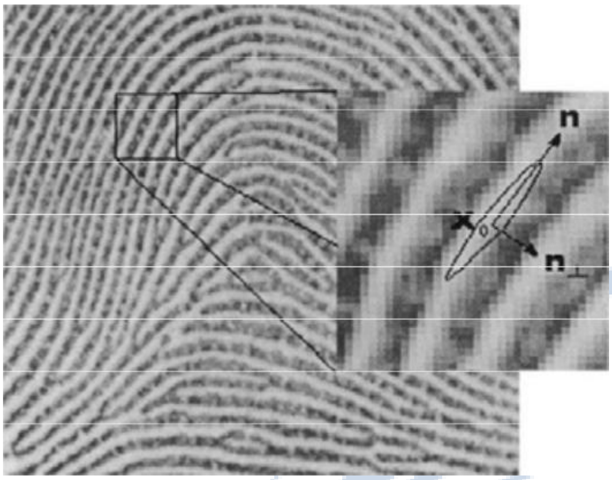

Fig 8: Anisotropic filter process

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

Table 1: values of the design parameters

7. CONCLUSION

Analyzing the DA architecture and performance, this paper presents a new architecture for DALUT. The proposed architecture applies the main concept of the basic DA technique in implementing the MAC unit and at the same time has many advantages over its basic architecture.

The prime logic units used in our proposed architecture is the carry lookahead adder and the tri-state buffer. The results obtained show that with the proposed architecture, the computation time and the area used is reduced. The proposed architecture can be easily used to implement high order FIR filters e.g. 20-tap with different coefficients wordlength without suffering from large LUT construction and with low hardware complexity needed for the design. The future work is to perform a VLSI implementation of pulse shaping FIR filter for ultra wideband communications.

REFERENCES

[1] A. Antonion, Digital Filters: Analysis, Design, and Applications, McGraw-Hill, New York, 1993.

[2] H.T. Kung, Why systolic architecture? IEEE Computer 15 (1) (1982) 37–45.

[3] S. Yu, E.E. Swartzlander, DCT implementation with distributed arithmetic, IEEE Transactions on Computers 50 (9) (2001) 985–991.

[4] Hanho Lee, Gerald E. Sobelman, FPGA-based digit-serial CSD FIR filter for image signal format conversion, Microelectronics Journal 33 (5–6) (2002) 501–508.

[5] Valeria Garofalo, Fixed-width multipliers for the implementation of efficient digital FIR filters, Microelectronics Journal 39 (12) (2008) 1491–1498.

[6] Lei Zhang, Tadeusz Kwasniewski, FIR filter optimization using bit-edge equalization in high-speed backplane data transmission, Microelectronics Journal 40 (10) (2009) 1449–1457.

[7] M. A. M. Eshtawie and M. Othman, On-line DA-LUT architecture for high-speed high-order digital FIR filters, in: Proceedings of the IEEE International Conference on Communication Systems (ICCS), Singapore, November. 2006,

[8] J. P. Choi, S.-C. Shin, and J.-G. Chung, Efficient ROM size reduction for distributed arithmetic, in: Proceedings of the IEEE International Symposium Circuits Systems (ISCAS), May 2000, pp. 61–64.

[9] Sanjay, Attri B. S., Sohi, and Y. C. Chopra, Efficient design of application specific DSP cores using FPGAs, in: International Conference on ASIC Proceedings, 2001, pp. 462-466.

[10] Kim Kyung-Saeng, Kwyro Lee, Low-power and area efficient FIR filter implementation suitable for multiple tape, IEEE Transactions on VLSI Systems 11 (1) (February 2003).