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Adaptive Fingerprint Image Enhancement Based on Spatial Contextual Filtering and Pre-processing of Data

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Abstract- Although fingerprint recognition technology has advanced rapidly there are still some challenging research problems. Research has been conducted to develop Automatic Fingerprint Identification Systems (AFIS). The main problem in automatic fingerprint identification is to acquire matching reliable features from poor quality fingerprint images. Another challenging problem is the processing and matching of overlapped fingerprints. So, this paper proposes several improvements to an adaptive fingerprint enhancement method that is based on contextual filtering. The term "adaptive" implies that parameters of the method are automatically adjusted based on the input fingerprint image. Five processing blocks comprise the adaptive fingerprint enhancement method, where four of these blocks are updated in our proposed system. Hence, the proposed overall system is novel.

The four updated processing blocks are: 1) preprocessing; 2) global analysis; 3) local analysis; and 4) matched filtering. In the preprocessing and local analysis blocks, a nonlinear dynamic range adjustment method is used. In the global analysis and matched filtering blocks, different forms of order statistical filters are applied. These processing blocks yield an improved and new adaptive fingerprint image processing method. There are situations where several fingerprints overlap on top of each other. A future enhancement is to separate such overlapped fingerprints into component fingerprints and enhance them so that existing fingerprint matchers can recognize them. The algorithm is evaluated toward the NIST developed NBIS software for fingerprint recognition on FVC databases.

Keywords- **Directional filtering, Fourier transform, image processing, spectral feature estimation, successive mean quantization transform**.

1. Introduction

Biometric recognition, or simply biometrics, refers to the use of distinctive anatomical and behavioral characteristics or identifiers such as fingerprints, iris, voice, hand-geometry, etc, for automatically recognizing a person. Traditional credential based systems no longer suffice to verify a person's identity since they can be easily misplaced, copied, or shared. Biometric identifiers are considered more reliable for person recognition than traditional token- (eg: keys, ID cards, etc.) or knowledge (eg: password, PIN, etc.) based methods. Biometric recognition provides better security, higher efficiency, and user convenience. A number of biometric technologies have been successfully deployed. Because of the distinctiveness (individuality) as well as cost and maturity of products, fingerprints are the most widely used biometric characteristics. Fingerprint recognition is a pattern recognition system. It is generally believed that the pattern on each finger is unique. Fingerprint is the reproduction of the exterior appearance of the fingertip epidermis. The most evident structural characteristic of a fingerprint is a pattern of interleaved ridges and valleys on the surface of a fingertip. Ridges are dark whereas valleys are bright. Matching fingerprint images is a very difficult problem, mainly due to the large variability in different impressions of the same finger (i.e., larger intra-class variations). The main factors responsible for intra-class variations are displacement, rotation, partial overlap, pressure and skin condition, noise, etc.

Historically, in law enforcement applications, the acquisition of fingerprint images was performed by using the so-called "ink-technique"; the subject's fingers were smeared with black ink and pressed or rolled on a paper card; the card was then scanned by using a general purpose scanner, producing a digital image. This kind of acquisition process is called offline sensing. Nowadays, most civil and criminal AFIS accept live-scanned digital images acquired by directly sensing the finger surface with an electronic fingerprint scanner (also called fingerprint reader). No ink is required in this method, and all that a subject has to do is to present his finger to a live-scan scanner.

2. Literature Survey

Fingerprint matching was used solely for forensic purposes and human experts performed the fingerprint analysis manually, until the 1960's. An in-depth survey of the development in fingerprint recognition is provided in [1]. It presents in detail recent advances in fingerprint recognition, including sensing, feature extraction, matching and classification techniques, synthetic fingerprint generation, biometric fusion, fingerprint individuality and design of secure fingerprint systems. [1] introduces automatic techniques for fingerprint recognition and provides comprehensive reference book on fingerprint. Research has been conducted the last 50 years to develop Automatic Fingerprint Identification System (AFIS). However, the main problem in automatic fingerprint identification is to acquire matching reliable features from fingerprint images with poor quality.

Contextual filtering is a popular technique for fingerprint enhancement, where topological filter features are aligned with the local orientation and frequency of the ridges in the fingerprint image. The first method utilizing contextual filter to enhance fingerprint images performed both the filter design and the filtering in the spatial domain [2], [3]. A procedure for filter design is described for enhancing fingerprint images [2]. Four steps of this procedure are: i) user-specification of appropriate image features, ii) determination of local ridge orientation throughout the image, iii) smoothing of this orientation image, and iv) pixel-by-pixel image enhancement by application of oriented, matched filter masks. The contribution of this work is to quantify and justify the functional relationship between image features and parameters so that the design process can be easily modified for different conditions of noise and scale. Application of the filter shows good ridge separation and continuity, and background noise reduction. In this method, the main filter is having a horizontally directed pattern designed based on four manually identified parameters for each fingerprint image. Additional directions were created by rotating the main horizontal filter while the filter size remained constant.

Other fingerprint enhancement methods employ directional Gabor or Butterworth bandpass filters where the filtering is performed in the frequency domain [4], [5]. A fast fingerprint enhancement algorithm is proposed in [4], which can adaptively improve the clarity of ridge and valley structures of input fingerprint images based on the estimated local ridge orientation and frequency. Here, a bank of Gabor filters is used. [5] Introduces a new fingerprint enhancement algorithm, for AFIS, based upon non-stationary directional and Fourier domain filtering. Butterworth filter is used here and the algorithm improves the speed and accuracy of a particular AFIS.

Second directional derivatives for filter design, and a method for selecting a suitable size of the local area, were presented in [6]. This approach relies on detecting the fingerprint ridges based on the sign of the second directional derivative of the digital image. A facet model is used in order to approximate the derivatives at each image pixel based on the intensity values of pixels located in a certain neighbourhood. The size of this neighbourhood determines the scale of the image details that are preserved. Here, a selection criterion for the neighbourhood size is developed that aims to preserve image details and remove small details from the enhanced image. Gabor filters play an important role in many application areas for the enhancement of various types of images and the extraction of Gabor features. Recently, a method based on curved Gabor filters that locally adapt the filter shape to the curvature and direction of the flow of the fingerprint ridges was introduced in [7]. Curved Gabor filters are used for enhancing curved structures in noisy images. This new type of Gabor filter design shows a potential in fingerprint image enhancement in comparison to classical Gabor filter methods. However the computational load is immense which inhibits its use in practical applications.

Another method that stands out from the classical directional filter design approaches was proposed in [8]. A robust algorithm allowing good recognition of low quality fingerprints with inexpensive hardware is used in this method. A threshold FFT approach is developed simultaneously to smooth and enhance poor quality images derived from a database of imperfect prints. Instead of requiring tuned parameters for each fingerprint image, the magnitude spectrum of each local area of the fingerprint image was directly used to filter the same local area in the frequency domain. The rationale behind this method is that the local magnitude spectrum carries properties similar to a matched filter, and by using the magnitude spectrum directly as a filter, dominant components related to ridges are amplified. It is noted that this approach provides a noise gain as well, which makes it less useful in practical situations.

Existing methods typically keep various parameters such as local area, constant. The strategy to keep parameters constant may fail in a real application where fingerprint image or sensor characteristics vary, thus yielding varying image quality. In addition, due to the spatially variable nature of fingerprints, it is crucial to have a sufficient amount of data in each local image area.

Hence, the local area size should adapt to the data present. Different fingerprint sensor resolutions provide different normalized spatial frequencies of the same fingerprint and this also requires adaptive parameters. Fingerprints captured with the same sensor may also vary depending on gender, age of the user, etc. The negative influence on fingerprint recognition system performance for individuals of different ages was demonstrated in [9] and the matching results of Db3 in FVC2000 [10]. FVC2000 competition attempted to establish the first common benchmark, allowing companies and academic institutions to unambiguously compare performance and track improvements in their fingerprint recognition algorithms. To compensate for varying fingerprint image characteristics and to achieve an optimal system performance, key parameters of most existing methods (eg, the size of the local area), need to be tuned manually for every fingerprint image. This manual tuning for each image is tedious and costly and automatic systems are therefore desirable. This project extends existing adaptive fingerprint enhancement system [11], [12], by incorporating new processing blocks to construct an improved novel system. The proposed method is based on spatial contextual filtering using matched directional filters. A non-linear dynamic range adjustment method is used as a preprocessing stage. Hence, the Successive Mean Quantization Transform (SMQT) [14], [15] is used as a dynamic range adjustment. 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. The SMQT adjusts the dynamic range adaptively and nonlinearly and it is configured by only one design parameter B. The employment of the SMQT algorithm for fingerprint enhancement with $B = 8$ has been previously proposed in [16]. Two quality indices, global and local, for fingerprint images, were proposed in [17]. In our method, a median filter is proposed in the global spectral analysis to further improve the estimation of the fingerprint's fundamental frequency. The median filter suppresses noise and it has also a grouping effect which aids the frequency estimation. The present method furthermore proposes to use local dynamic range adjustment to improve local spectral features estimation. [17] Observed that, global index has better predictive capabilities at the image enhancement stage than local index, since the image enhancement algorithm is based on filtering in the frequency domain, and is therefore directly related to global index. Local index is slightly more effective than global index at the feature extraction stage, since feature extraction concentrates on local details which are measured directly by local analysis. Both global and local analyses are effective in predicting and improving the matching performance. An improvement for the existing adaptive fingerprint enhancement system which is based on preprocessing of data is proposed in [18].The evaluation focuses on the complete assessment of the proposed method's performance using the NBIS (NIST Biometric Image enhancement Software) for fingerprint recognition, developed by NIST(National Institute of Standards and Technology) [13].

3. Proposed Method

Five processing blocks comprise the adaptive fingerprint enhancement method; these are: 1) preprocessing 2) global analysis 3) local analysis 4) matched filtering and 5) image segmentation. In our proposed system, the first four blocks are updated by incorporating new processing blocks to make the overall system novel. The proposed method is based on spatial contextual filtering using matched directional filters. In the preprocessing and local analysis blocks, a nonlinear dynamic range adjustment method is used. In the global analysis and matched filtering blocks, different forms of order statistical filters are applied. These processing blocks yield an improved and new adaptive fingerprint image processing method. The algorithm is evaluated toward the NIST (National Institute of Standards & Technology) developed NBIS (NIST Biometric Image Software) software for fingerprint recognition on FVC (Fingerprint Verification Contest) database. The major advantage of the proposed method is that it is adaptive towards sensor and fingerprint variability. This method combines and updates existing processing blocks into a new and robust fingerprint enhancement system and this is particularly pronounced on fingerprint images having a low quality image.

3.1 Directional Filtering

Two-dimensional (2-D) edge detection can be performed by applying a suitably selected optimal edge half-filter in n directions. Computationally, such a two-dimensional n-directional filter can be represented by a pair of real masks, that is, by one complex-number matrix, regardless of the number of filtering directions, n:

Specific calculations of the edge strength were conducted using a 2-D tridirectional filter based on a Petrou–Kittler one-dimensional (1-D) detector optimized for the ramp edges, which are characteristic of posterior eye capsule images that were used here as a test set. In applications to image segmentation, tridirectional filtering results in co-occurrence arrays of low dimensionality.

3.2 Fourier Transform

The Fourier Transform is a mathematical transformation employed to transform signals between time (or spatial) domain and frequency domain, which has many applications in physics and engineering. It is reversible, being able to transform from either domain to the other. The term itself refers to both the transform operation and to the function it produces. In the case of a periodic function over time (for example, a continuous but not necessarily sinusoidal musical sound), the Fourier transform can be simplified to the calculation of a discrete set of complex amplitudes, called Fourier series coefficients. They represent the frequency spectrum of the original time-domain signal. Also, when a time-domain function is sampled to facilitate storage or computer-processing, it is still possible to recreate a version of the original Fourier transform according to the Poisson summation formula, also known as discrete-time Fourier transform.

3.3 Successive Mean Quantization Transform (SMQT)

Successive Mean Quantization Transform (SMQT) reveals the organization or structure of the data and removes properties such as gain and bias. The transform is described and applied in speech processing and image processing. In image processing the transform is applied in automatic image enhancement and dynamic range compression.

Histogram equalization automatically flattens and stretches the dynamic range of the histogram of the image. Hence, an enhancement of the contrast in the image is achieved. The Successive Mean Quantization Transform (SMQT) has properties that reveal the underlying structure in data. The transform performs an automatic structural breakdown of information. This can be interpreted as a progressive focus on details in an image. These characteristics make the transform interesting for automatic enhancement of any image. In this paper the SMQT is applied and examined for automatic image enhancement. The transform is presented using set theory. An adjustment parameter is introduced to further control the enhancement. The nonlinear properties of the transform are investigated by means of the histogram.

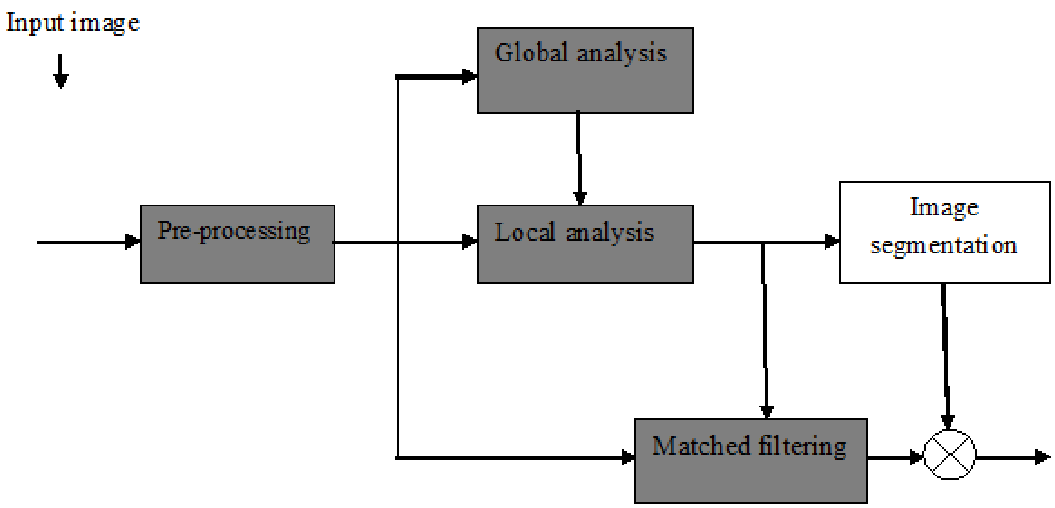

Fig.1. Processing blocks of the proposed method. Gray blocks: updated processing blocks.

The proposed fingerprint enhancement method is based on an existing method .Here, key processing blocks are updated by additional new processing stages so as to yield a novel enhancement system, see Fig. 1.First, an innovative non-linear preprocessing block adjusts the dynamic range of the image. Second, a novel update to the previously derived global fingerprint analysis is conducted to aid the fundamental spatial frequency estimation of the fingerprint image, and where a data-outlier suppression further improves the frequency estimation performance for noisy images. Third, based on the estimated fundamental frequency from the global analysis, a local adaptive analysis adjusts the fundamental frequency to match the local image area. The local analysis proposes the use of a local dynamic range adjustment method to further improve spectral features estimation. Fourth, the matched filtering is based on the spectral features estimated in the local analysis, where an additional order-statistical filtering of the spectral features is introduced to increase the method's resilience towards noise. Finally, an image segmentation separates fingerprint data from the background. This, taken all together, comprises the proposed new fingerprint enhancement system that automatically tunes its parameters according to each individual fingerprint image.

A. Preprocessing

Let I (n1, n2) represent a fingerprint image of size N1×N2, where n1 ϵ [0, N1 − 1] and n2 ϵ [0, N2 − 1] denote horizontal and vertical coordinates (local area indices), respectively. Without loss of generality, each element of I (n1, n2) is assumed to be quantized in 256 (i.e., 2^8) gray-scale levels, i.e., the dynamic range of the image is eight bits. However, the fingerprint image may not use the full dynamic range in a practical situation and this may degrade system performance. The Successive Mean Quantization Transform (SMQT) is used as a dynamic range adjustment here. 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. This nonlinear property of SMQT yields a balanced image enhancement. Thus, the SMQT adjusts the dynamic range adaptively and nonlinearly and it is configured by only one design parameter B. The parameter B corresponds to the number of levels in the binary tree and is equal to the number of bits used to represent the SMQT processed image. The nonlinear SMQT-operation is denoted as SMQTB { }. The parameter is set to B = 8 in the preprocessing stage, which means that the dynamic range adjustment provided by the SMQT-operation does not alter the bit-depth of the enhanced fingerprint image. The preprocessed eight-bit SMQT image is denoted as X(n1, n2) = SMQT8 {I (n1, n2)}, where the notation X means that this enhanced image acts as input to further processing.

Large regional contrast variation is quite typical for low quality fingerprint images which require a high dynamic range usage in order to not embed fingerprint ridges in the background. Hence, the SMQT-enhancement is performed using eight bits so as to avoid the risk of obstructing important data in heavily noisy fingerprint images. In addition, the eight-bit SMQT used in the preprocessing requires only a fractional amount of processing as opposed to other parts of the proposed method .Optimizing the processing load on this part of the algorithm yields therefore only an insignificant reduction of processing power but increases the risk of reduced performance.

B. Global Analysis

This is employed to estimate the fundamental spatial 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. The fundamental fingerprint frequency is estimated in the global analysis according to the following steps:

1) Data Outlier Suppression: A new processing stage suppresses data outliers by a median filter. Here, a 3×3 median filter is applied to the SMQT enhanced image in order to suppress data outliers. The median filtered fingerprint image is denoted as Z (n1, n2) = Median3×3 {X (n1, n2)}.

2) Radial Frequency Histogram: A radial frequency histogram is computed from the magnitude spectrum of the median filtered image. Let F (ω1, ω2) = F {Z (n1, n2)} denote the two-dimensional Fourier transform of the preprocessed and median filtered input image Z (n1, n2), where, ω1 ϵ [−π, π) and ω2 ϵ [−π, π) denote normalized frequency. The spectral image is represented in polar form for clarity in the presentation, i.e., F (ω1, ω2) ≡ F (ω, θ), related through the following change of variables ω1 = ω · cos θ and ω2 = ω · sin θ, where ω is the normalized radial frequency and θ denotes the polar angle. A radial frequency histogram A (ω) is obtained by integrating the magnitude spectrum |F (ω, θ)| along the polar angle θ, according to

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

3) Fundamental Frequency Estimation: The fundamental frequency of the fingerprint is assumed located at the point where the radial frequency histogram attains its maximal value. The radial frequency histogram may contain impulsive noise due to noisy input signals. So, the radial frequency histogram is herein proposed to be smoothed in order to reduce the impact of spurious noise. Therefore a smoothing filter is employed here which perform smoothing along the ω-variable in A (ω), to suppress the impulsive noise, where the smoothed radial frequency histogram is denoted as AS (ω). The radial frequency at the point where the radial frequency histogram attains its largest value corresponds to the fundamental frequency ωf of the fingerprint image, i.e.,

$$\omega f = \arg \max_{\omega \epsilon [\omega\, min,\, \pi]} AS(\omega) \qquad (2)$$

The lower boundary ω min is introduced in order to avoid erroneous peak values related to low frequency noise. Empirical analysis shows that there are at least 10 full periods of the fingerprint pattern in an image. Hence, the lower boundary is computed as

$$\omega\ min = (2 \cdot \pi \cdot 10) / \max(N1, N2) \qquad (3)$$

The fundamental frequency ω f, computed in Eq. 2, is inversely proportional to a fundamental area size L f , according to

$$L\ f = (2\pi)/(\omega\ f) \qquad (4)$$

C. Local Analysis

The purpose of the local analysis is to adaptively estimate local spectral features corresponding to fingerprint ridge frequency and orientation. Most parts of a fingerprint image containing ridges and valleys have, on a local scale, similarities to a sinusoidal signal in noise. Hence, they have a magnitude spectrum with two distinct spectral peaks located at the signal’s dominant spatial frequency, and oriented in alignment with the spatial signal. 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. 4 is used as a fundament in the local analysis. The size of the local area in the local analysis is M × M, where M is an odd-valued integer. Due to the local variability of a fingerprint, for example in regions around deltas, cores and minutiae where the fingerprint ridges are curved or when the local ridge frequency deviates from the estimated fundamental frequency ω_f , two additional local area sizes are introduced. 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. 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 following steps are carried out for each local area in the local analysis:

1) Local Dynamic Range Adjustment: A local dynamic range adjustment is proposed to be applied to each local area. Low quality fingerprint images usually consist of regions with a poor contrast between signal (i.e., fingerprint pattern), and background. This poor contrast may remain in some local areas even after global contrast enhancement. Local image areas having a poor contrast yield unsatisfactory local features extraction due to the low signal to noise ratio. A local contrast enhancement is therefore proposed herein by applying the SMQT dynamic range adjustment method on each local image area according to $H(m1, m2) = SMQT_2 \{J(m1, m2)\}$. It is noted that, the local analysis is based on local areas $J(m1, m2)$ of the globally SMQT processed $X(n1, n2)$ image.

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. This stands out from the eight bits used in the dynamic range adjustment in the preprocessing stage. The local areas enhanced by a two-bit SMQT (B = 2) and an eight-bit SMQT (B = 8) are close to identical, however, where the lower value B = 2 requires less computational resources and is therefore preferred in a practical implementation.

2) Data Transformation, Windowing, Zero Padding: A data-driven transformation is conducted in order to improve local spectral features estimation. The data for each local area is windowed and zero padded to the next larger power of two. The local analysis uses a spatial window to suppress spectral side-lobes. The use of a window may yield feature estimation errors if a fingerprint valley is in the center of the local area since the window suppresses adjacent ridges. Hence, the dominant peak will be suppressed in the frequency spectrum as well. A suitable test will be conducted to resolve this problem. 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 center of the local image area.
In order to improve local features extraction, the frequency spectrum has to have an adequate resolution. Therefore, each transformed local area is zero padded to the next higher power of two since an FFT is used to frequency-transform the image. To reduce the magnitude of spectral side-lobes, a two-dimensional Hamming window is applied to the local area, smoothing the transition between data and the zero-padding.

3) Spectral Features Estimation: A local magnitude spectrum is obtained by computing the modulus of the two-dimensional Fourier transform of the transformed, zero-padded and windowed local area and the dominant spectral peak is located from which the local features frequency, orientation and magnitude are estimated.

4) Local Area Re-examination Test: A test if the local area needs to be re-examined, using a larger and a smaller size of the local area, is conducted. 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 , may yield inaccurate spectral features estimates. These regions are re-examined using two additional sizes of the local area. Steps 1–3 of the local analysis are repeated using these alternative area sizes if a re-examination is required.

D. Matched Filtering

A local area that contains a fingerprint image pattern is highly periodic and it therefore renders a strong dominant peak. The estimated local features are the vertical and horizontal spatial frequencies of the local dominant spectral peak. The estimated frequencies are occasionally 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 estimated frequencies is thus performed to reduce the impact of this noise. The smoothing is performed by filtering using order statistical filters, so called α-trimmed mean filter, along the n1, n2-dimensions.

E. Image Segmentation

Fingerprint scanners have various sizes of the sensor area. This renders that fingerprint patterns obtained by a fingerprint scanner with a large sensor area only occupy

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a part of the image, as opposed to a scanner with a small sensor area. To suppress non-relevant parts of a fingerprint image, i.e., where there is no fingerprint data, a segmentation of the image is performed. Here, the segmentation of the fingerprint image is performed by applying a binary mask to the fingerprint image. The segmentation method used here is identical to that in the existing system, 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, in accordance with the existing method. The output image is the element-wise product of the binary mask and the matched filter output signal, i.e., Y (n1, n2).

4. Evaluation

Five processing blocks comprise the adaptive fingerprint enhancement method; these are: 1) preprocessing 2) global analysis 3) local analysis 4) matched filtering and 5) image segmentation. Several improvements to an adaptive fingerprint enhancement method that is based on contextual filtering are done here. In our proposed system, the first four blocks are updated by incorporating new processing blocks to make the overall system novel. So, this project extends previous work by focusing on preprocessing of data on a global and a local level. A preprocessing using the non-linear SMQT (Successive Mean Quantization Transform) dynamic range adjustment method is conducted to enhance the global contrast of the fingerprint image prior to further processing. The transform is capable perform both a nonlinear and a shape preserving stretch of the image histogram. Histogram equalization automatically flattens and stretches the dynamic range of the histogram of the image. Hence, an enhancement of the contrast in the image is achieved. The SMQT has properties that reveal the underlying structure in data. Here, each element of the fingerprint image is assumed to be quantized in 256 (i.e., 2^8) gray-scale levels, i.e., the dynamic range of the image is eight bits. 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. Thus, the SMQT adjusts the dynamic range adaptively and nonlinearly and it is configured by only one design parameter B. The parameter B corresponds to the number of levels in the binary tree and is equal to the number of bits used to represent the SMQT processed image. Large regional contrast variation is quite typical for low quality fingerprint images which require a high dynamic range usage in order to not embed fingerprint ridges in the background. Hence, the SMQT-enhancement employed here is performed using eight bits so as to avoid the risk of obstructing important data in heavily noisy fingerprint images. The parameter is set to B = 8 in the preprocessing stage. Hence, the dynamic range adjustment provided by the SMQT-operation does not alter the bit-depth of the enhanced fingerprint image. This enhanced image is taken as input to further processing.

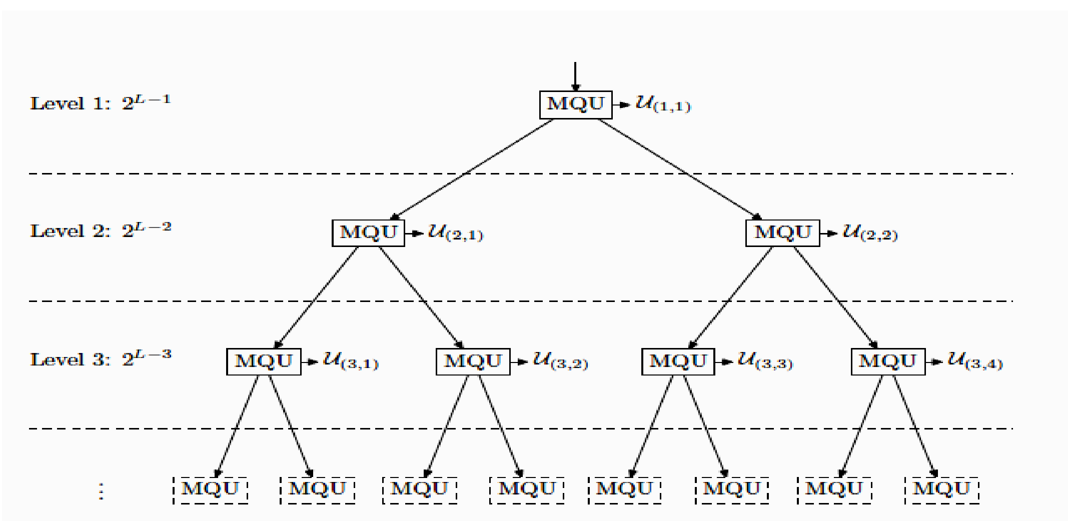

Fig.2. The SMQT as a binary tree of Mean Quantization Units (MQUs).

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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. A 2-D median filter is employed as a new processing block here. It is used to suppress the data outliers. The function medfilt2 (A, [m n]) performs median filtering of matrix A in two dimensions. Each output pixel contains the median value in the m×n neighbourhood around the corresponding pixel in the input image.medfilt2 pads the image with 0s on the edges, so the median values for the points within [m n] / 2 of the edges might appear distorted. The function medfilt2 (A) used here, performs median filtering of matrix A using the default 3×3 neighbourhood. Then the 2-D Fourier Transform of the preprocessed and median filtered fingerprint image, is carried out. A radial frequency histogram is computed from the magnitude spectrum. A smoothing process is also conducted in order to suppress the impulsive noise contained in the radial frequency histogram. The fundamental frequency ω f is calculated, where the radial frequency histogram attains its largest value.

A local contrast enhancement is performed by a low-order SMQT dynamic range adjustment method (SMQT2) in the local adaptive analysis stage. It is used to achieve reliable features extraction used in the matched filter design and in the image segmentation. The purpose of the local analysis is to adaptively estimate local spectral features corresponding to fingerprint ridge frequency and orientation. 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. The local areas enhanced by a two-bit SMQT (B = 2) and an eight-bit SMQT (B = 8) are close to identical, however, where the lower value B = 2 requires less computational resources.

Fig. 3. Examples of the proposed fingerprint enhancement method. (a) Original images, (b) Enhancement with the original method, (c) Enhancement with the proposed method.

5. Future Scope

Also, as a future enhancement work, overlapped fingerprints can be separated based on the proposed method. There are situations where several fingerprints overlap on top of each other. Such situations are frequently encountered when latent (partial) fingerprints are lifted from crime scenes or residue fingerprints are left on fingerprint sensors. Overlapped fingerprints constitute a serious challenge to existing fingerprint recognition algorithms. Thus, a future enhancement is to separate such overlapped fingerprints into component fingerprints and enhance them so that existing fingerprint matchers can recognize them.

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Fig. 4. Image with three overlapping fingerprints.

6. Conclusion

This paper presents an adaptive fingerprint enhancement method. The method extends previous work by focusing on preprocessing of data on a global and a local level. A preprocessing using the non-linear SMQT dynamic range 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. 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 proposed method combines and updates existing processing blocks into a new and robust fingerprint enhancement system. The updated processing blocks lead to a drastically increased method performance. The proposed method improves the performance in relation to the NIST method, and this is particularly pronounced on fingerprint images having a low image quality. The proposed algorithm is insensitive to the varying characteristics of fingerprint images obtained by different sensors.

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