International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Fingerprint Image Enhancement Using Adaptive Pre-processing of Data and K-means Segmentation

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Abstract: ***An adaptive fingerprint image enhancement method is proposed in this paper. Which is the improvement of existing methods based on contextual filtering. Adaptive system implies the parameters of this method are automatically adjusted based on input fingerprint image. Method is comprised into five processing blocks where all the five blocks are updated with new and best technologies. Hence over all system is noval. Processing blocks are preprocessing, global analysis, local analysis, matched filtering and image segmentation. a non linear dynamic range adjustment method is performed in preprocessing and local analysis blocks. Different form of order statistical filtering are applied in global analysis and matched filtering. A new technique called K-means segmentation is used for image segmentation. These processing blocks yield an improved and new adaptive fingerprint image processing method. The performance of updated processing blocks is presented in evaluation part of this paper.***

Keywords: Directional filtering, Fourier transform, image processing, spectral feature estimation, successive mean quantization transform

1. Introduction

The popular technology in fingerprint image enhancement is contextual filtering. According to the local orientation and frequency of the ridges in the fingerprint image the topological filter features are aligned. The first method performed in spatial domain for both filter design and filtering which utilizes the contextual filters to enhance fingerprint image [2],[3]. In that method for each fingerprint image a horizontally directed pattern designed based on four manually identified parameters. By making filter size constant, additional directors were created by performing rotation to main horizontal filter. Other method in fingerprint image enhancement utilize directional Butterworth or Gabor band pass filters were filter design and filtering are performed in frequency domain [4][5]. In another method of fingerprint image enhancement second directional derivative for filter designed were used for selecting a suitable size of local area [6]. A recent technology locally adapts the filter shape to the curvature and the direction of flow of the fingerprint ridges were introduced and that was based on curved Gabor filters [7]. This new technology of Gabor filter method. But the computational load is much larger than existing system which inhibits its use in practical cases.

Another method better than classical directional filter design performed a new technique. To filter each local area in frequency domain the magnitude spectrum of each local area was directly choose instead of requiring tuned parameters for each fingerprint images. The importance of this method is that the local magnitude spectrum of fingerprint image carries properties similar to matched filter, so dominant components related to ridges are amplified. Also the method provides a noise gain which makes its useless in practical applications.

All existing methods keeps the parameters constant such as local image area. By keeping parameters constant may fail in real applications were sensor characteristics or fingerprint images vary, thus yielding varying image quality. Also fingerprint has spatially variable nature so when choosing a local image area its crucial to have sufficient amount of data. Hence the local area size should adopt to the data present in it. Adaptive parameters are required in the case of different fingerprint sensors because different sensors resolution gives different spatial frequencies of same fingerprint.

An improved noval system is proposed in this article which extends existing adaptive fingerprint image enhancement methods. By introducing new and better processing blocks in preprocessing of data. This fingerprint image enhancement method is based on spatial contextual filtering by using matched directional filters. in pre processing stage a non-linear dynamic range adjustment of fingerprint image is used. Medien filters are used for outlier suppression in global analysis which useful for estimating fundamental frequency of fingerprint . With respect to fundamental frequency adaptively chose local image area to estimate local spectral features. A noval image segmentation technique also proposed in this paper.

2. Proposed Method

1) Introduction

The proposed fingerprint enhancement method is based on an existing method. However, key processing blocks are updated by additional new processing stages so as to yield a novel enhancement system. First, a 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 determine the fundamental spatial frequency estimation of the fingerprint image, and where a data-outlier suppression further improves the frequency estimation performance for noisy images. Then 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, a K-means segmentation method is used for image segmentation to 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 hence called adaptive.

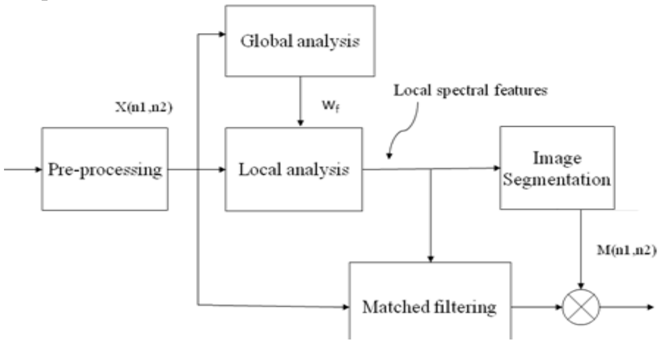
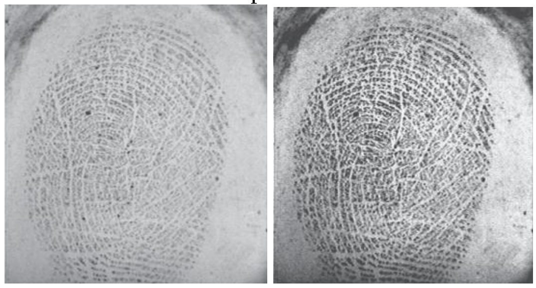


Figure 1: Block diagram

2) Preprocessing

Let a fingerprint image of size $N1\times N2$ represent $I(n_1, n_2)$ where $n1$ denote horizontal and vertical coordinates, respectively. The dynamic range of the image is eight bits each element of $I(n_1, n_2)$ is assumed to be quantized in 256 gray-scale levels. However, the fingerprint image may not use the full dynamic range in a practical situation and this may degrade system performance. A method called The Successive Mean Quantization Transform (SMQT)[8][9] is used as a dynamic range adjustment in this paper. The SMQT is a binary tree build of a simple Mean Quantization Units 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 is equivalent to a nonlinear histogram stretch while still preserving basic histogram shape. This nonlinear property of SMQT yields a balanced image enhancement. 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 $\text{SMQT}_B\{\ \}$. The parameter is set to $B = 8$ in the preprocessing stage of this paper, 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 $X(n_1,n_2)=\text{SMQT}_8\ \{I\ (n_1,\ n_2)\}$, 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.

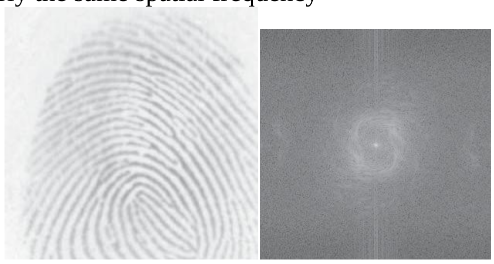


(a) (b)

Figure 2: (a) Fingerprint image and (b) corresponding SMQT enhanced image. Both images have eight-bit dynamic range.

3) Global Analysis

The magnitude spectrum of a fingerprint image typically in shape of circular structure around the origin, see the example in Fig. 3. The circular structure stems from the throughout the image but varying local orientation. The circular structure in the magnitude spectrum has been used for estimating fingerprint quality[10][11]. The circular spectral structure was exploited to detect the presence of a fingerprint pattern in the image[12]. 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. The fundamental fingerprint frequency is estimated in the global analysis according to the following steps (see a block schema in Fig. 4). fact that a fingerprint has nearly the same spatial frequency



(a) (b)

Figure 3: (a) Fingerprint image and (b) corresponding magnitude spectrum.The circular structure around the origin in the fingerprint magnitude spectrum.

1) A new processing stage suppresses data outliers by a median filter.
2) A radial frequency histogram is computed from the magnitude spectrum of the median filtered image.
3) 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 is herein proposed to be smoothed in order to reduce the impact of spurious noise.

1) Step 1 - Data-Outlier Suppression: This paper proposes to apply a 3×3 median filter to the SMQT enhanced image in order to suppress data outliers. The median filtered fingerprint image is denoted as $Z(n_1, n_2)$ = Median3×3 $\{X(n_1, n_2)\}$.

2) Step 2 - Radial Frequency Histogram: Let $F(\omega_1,\omega_2) = F\{Z(n_1, n_2)\}$ denote the two-dimensional Fourier transform of the preprocessed and median filtered input image $Z(n_1, n_2)$, where, $\omega_1 \in [-\pi, \pi)$ and $\omega 2 \in [-\pi, \pi)$ denote normalized frequency. The spectral image is represented in polar form for clarity in the presentation, 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.

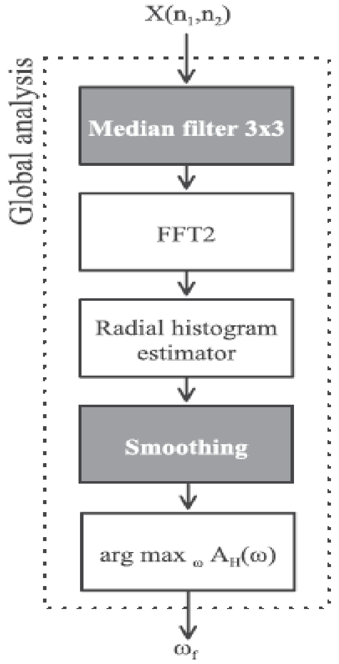


Figure 4: Processing blocks of the global analysis. Gray blocks: novel processing blocks.

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

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

where, due to the complex conjugate symmetry of $F(\omega, \theta)$, it is sufficient to integrate only over one half-plane in Equation 1

3) Step 3 - Fundamental Frequency Estimation: The radial frequency histogram may contain impulsive noise due to noisy input signals. This paper therefore proposes employing a smoothing filter which smoothing done along the ω-variable in $A(\omega)$ to suppress the impulsive noise, where the smoothed radial frequency histogram is denoted as $A_S(\omega)$. 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, i.e.,

$$\omega_f = \arg\max_{\omega \in [\omega_{min}, \pi]} A_S(\omega) \quad (2)$$

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 search boundary is computed as

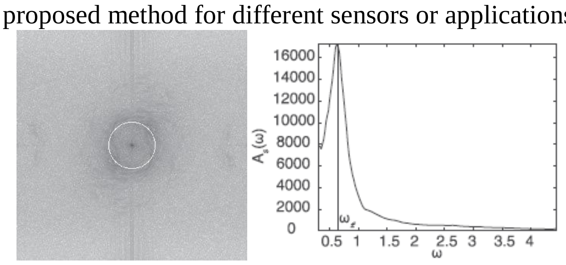
$$\omega_{min} = \frac{2 \cdot \pi \cdot 10}{\max(N1, N2)} \quad (3)$$

For practical reasons, the radial frequency is made discrete in the implementation, and a five point FIR filter with the Z-transform $H(z) = \frac{1}{5}(1 + z^{-1} + z^{-2} + z^{-3} + z^{-4})$ is used to smooth the radial frequency histogram. One example of a fingerprint magnitude spectrum together with a corresponding radial frequency histogram is illustrated in Fig. 5.

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

$$L\,f = \frac{2\pi}{\omega f} \quad (4)$$

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.



(a) (b)

Figure 5: Fingerprint magnitude spectrum with an overlayed circle whose radius corresponds to the (a) estimated fundamental frequency $\omega\,f$ and the corresponding radial-frequency histogram $As(\omega)$ whose peak value is located at (b) the fundamental frequency.

4) Local Adaptive 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. A similar method based on local spectral analysis is described in [13][14]. However, according to the evaluation, there are distinct performance improvements in the proposed method.

The fundamental area size L_f computed in Eq. 4 is used as a fundament in the local analysis, see Fig. 6. The size of the local area in the local analysis is $M \times M$, where M is an odd-valued integer computed as

$$M = 2\left\lfloor \frac{kLf}{2} + 1 \right\rfloor - 1 \quad (5)$$

where the parameter k is a design parameter that controls the number of fundamental periods enclosed by each local area.

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. 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 is illustrated in Fig. 7. Similar methods that incorporate multi-size windows or fingerprint image scaling are proposed in[15]-[17]. 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 preprocessed image $X(n_1, n_2)$ according to

$Jn_1,n_2\ (m_1,m_2) = X(n_1 + m_1, n_2 + m_2)$ (6)

where $m_1 = \left(-\frac{M-1}{2} \ldots \frac{M-1}{2}\right)$ and $m_2 = \left(-\frac{M-1}{2} \ldots \frac{M-1}{2}\right)$ are 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., $Jn_1,n_2\ (m_1,m_2) \equiv J\ (m_1,m_2)$. The following steps are carried out for each local area in the local analysis:

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 is windowed and zero padded to the next larger power of two

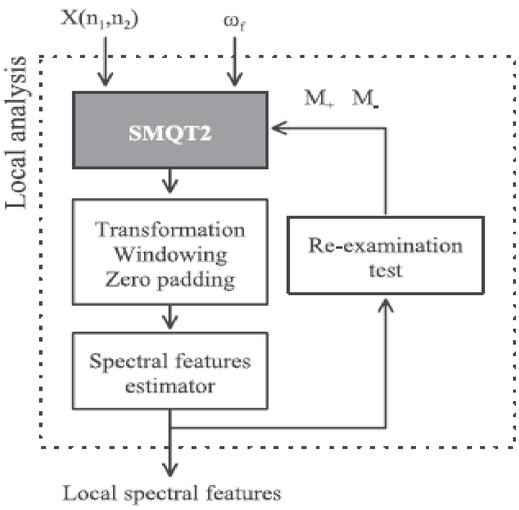


Figure 6: Processing blocks of the local adaptive analysis. Gray blocks: novel processing blocks.

Figure 7: Example of local area size $M\times M$, and corresponding sizes after growth $M_+\times M_+$ and shrinkage $M_-\times M_-$.

3) A local magnitude spectrum is computed and the dominant spectral peak is located from which the local features frequency, orientation and magnitude are estimated.
4) A test if the local area needs to be reexamined, using a larger and a smaller size of the local area, is conducted. Steps 1–3 of the local analysis are repeated using these alternative area sizes if a reexamination is required.

1) Step 1 - Local Dynamic Range Adjustment: 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 $H(m_1,m_2)$ = $\text{SMQT}_2\ \{J\ (m_1,m_2)\}$. It is noted that, the local analysis is based on local areas $J\ (m_1,m_2)$ of the globally SMQT-processed $X(n_1, n_2)$ 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: 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 simple test triggers a data-transformation that circumvents this problem.

3) Step 3 - Spectral Features Estimation: A local magnitude spectrum $G(\omega_1,\omega_2)$ = $|\mathrm{F}\ \{H(m_1,m_2)\}|$ 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 P_D and frequencies $\omega D,1$, $\omega D,2$ of the dominant spectral peak and the magnitude of the second largest spectral peak P_{D2}. A quality measure is computed based on the extracted features. The measure $\frac{PD}{P\max}$ quantifies the significance of the largest peak in relation to $P\max$, the maximum magnitude possible including the bias of the window. The measure $\frac{PD2}{PD}$ assesses the relationship between the two largest spectral peaks, P_D and P_{D2}, found in the magnitude spectrum of each local area. If the local area contains a dominant narrowband signal, such as a fingerprint pattern, $\frac{PD}{Pmax}$ will be close to unity and $\frac{PD2}{PD}$ will be close to zero.

4) Step 4 - Local Area Reexamination 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 ω_f , may yield inaccurate spectral features estimates. These regions are reexamined using two additional sizes of the local area.

A reexamination 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 reexamination 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.

5) 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 $\omega_{D,1}$ and $\omega_{D,2}$ represent, respectively, the vertical and horizontal spatial frequencies of the local dominant spectral peak.

The estimated frequencies $\omega_{D,1}$ and $\omega_{D,2}$ 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 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 $\omega_D = \sqrt{\omega^2 D,1 + \omega^2 D,2}$ θD =arctan $(\frac{\omega D,2}{\omega D,1})$. The smoothing is performed by filtering ω_D and θ_D using order statistical filters, so called α-trimmed mean filter, along the n_1, n_2-dimensions.

The α-trimmed mean filter uses an observation window, of size $2L+1\times 2L+1$ where $L=\lfloor \gamma \cdot Lf \rfloor$ 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., $\alpha\cdot(2+1)^2$ 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 $\tilde{\omega}_{D,2}=\tilde{\omega}_D\cdot\sin\tilde{\theta}_D$. The smoothed spatial frequencies are used to construct a filter $f\ (m_1,m_2)$, where $(m_1,m_2)\in[-N, N]$, matched to the local area at hand. The size of the filter is selected as $2N+1\times 2N+1$.

6) Image Segmentation.

Traditional statistical image segmentation algorithms, as simple as thresholding or as complicated as K-mean and even fuzzy K-mean clustering, all classify the pixels into clusters based only on their intensity values. Each cluster is usually characterized by a constant intensity and no spatial constraint is imposed. In practice, images are usually noise contaminated versions of the reflected density function, and the image intensity of the same class may change over space due to some physical constraints of the imaging system as we have discussed. In many biomedical applications, even though the relative intensity is evident for different clusters within a small neighborhood, different clusters at different locations may have similar intensity appearance due to the inhomogeneous nature of the imaging media. Therefore, a single global threshold is usually inapplicable to such images even within the same 2-D cross-section. The ability of being adaptive to the local intensity distribution is generally required for a robust image clustering algorithm to obtain the correct clustering results. In addition, certain spatial constraints are needed to prevent the algorithm from misclustering caused by the impulse noise introduced in the process of image acquisition and reconstruction. Such spatial constraint is based on the assumption that a pixel generally tends to belong to same cluster as most of its neighbors unless it is on the edge of a sharp region transition.

With the successful application of Markov random field in image segmentation, several extensions to the traditional K-mean clustering algorithm based on Gibbs random fields have recently been proposed. These extensions have included the spatial constraints through the modeling of the spatial distribution of the clusters as Gibbs random fields. Such modeling of spatial distribution indeed imposes the spatial continuity in the process of clustering and produces more robust results than traditional -mean algorithm. However, they all assume that the intensity or its related parameters would be constant within each clustered region. The adaptive -mean algorithm we develop is based on the segmentation algorithm proposed recently by Pappas. His algorithm includes not only the 2-D spatial constraints characterized by Gibbs random fields, but also the adaptive capability specified through iterative estimation of local means of each region. We have extended Pappas' algorithm through the development of 3-D spatial constraints to suit the volumetric nature of the image data and an enhanced adaptive capability to account for the varying characteristics of the cluster means as well as cluster variances.

3. Result

Three examples of results are shown in figure Fig. 8. The qualities of fingerprint images and fingerprint sensor characteristics have a great influence on the performance of a fingerprint matching system. It is therefore common to employ

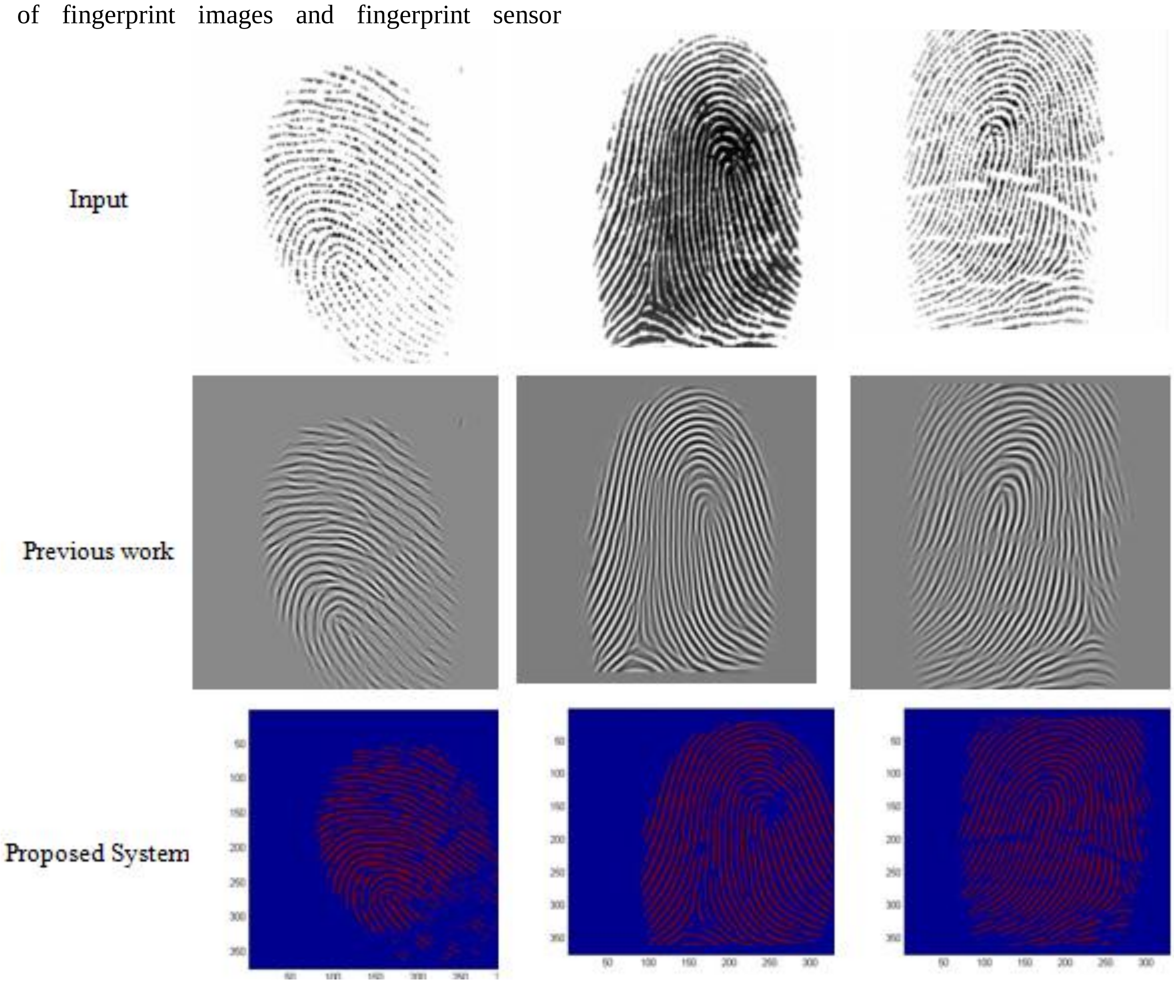


Figure 8: Comparison of previous work and proposed system.

Fingerprint enhancement to increase the image quality and to improve the matching performance. In this paper, the proposed enhancement method is compared with three similar methods based on contextual filtering. Contextual filtering methods are dependent on locally estimated features such as fingerprint ridge frequency, orientation, and curvature, where these features are used to perform matched filtering locally. The feature estimation accuracy constrains how well these methods work, and one dominating factor is the size of the analysis window that is the local area size, in relation to the characteristics of the fingerprint image.

The method proposed in this paper performs better than the method proposed by previous on the FVC2002 Db3a database. Both methods are based on the same principle. That is, they estimate the local features by frequency analysis. The main difference is that the previous method has a block based processing with a fixed size of the local area and do not employ the adaptive window size that is used in our work, leading to unsatisfactory feature estimates. Also the method does not employ any nonlinear contrast enhancement on a global or a local level.

The proposed method shows an improvement on three out of four FVC2004 databases in comparison to the method. The pyramid decomposition of the fingerprint image is to some extent related to the multi-size window reexamination in our paper.

The main restriction of the pyramid decomposition approach is that it is based on the size of the image and not on the image content, that is., the fingerprint characteristics. Enhancement of the fingerprints with a fundamental ridge frequency near or outside of the assumed boundary ridge frequency will be reduced. The application of the proposed estimated fundamental frequency in the pyramid decomposition could further improve the performance of the method.

4. 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. Image segmentation is done by K-means algorithm. 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 where the EER is improved by a factor two, and the AAC is improved by a factor 12, in relation to the original method. 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 evaluation results indicate that the method is able to adapt to varying fingerprint image qualities, and it is stressed that the proposed method has not been tuned in favor towards any database.

A possible future research direction is to perform a detailed and systematic analysis of the impact of the different chosen design parameters. Furthermore, various optimizations of the implemented processing steps could reduce the number of instructions required by the proposed method.

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