Pyramid-based Image Enhancement of Fingerprints

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Abstract

Reliable feature extraction is crucial for accurate biometric recognition. Unfortunately feature extraction is hampered by noisy input data, especially so in case of fingerprints. We propose a method to enhance the quality of a given fingerprint with the purpose to improve the recognition performance. A Laplacian like image-scale pyramid is used for this purpose to decompose the original fingerprint into 3 smaller images corresponding to different frequency bands. In a further step, contextual filtering is performed using these pyramid levels and 1D Gaussians, where the corresponding filtering directions are derived from the frequency-adapted structure tensor. All image processing is done in the spatial domain, avoiding block artifacts while conserving the biometric signal well. We report on comparative results and present quantitative improvements, by applying the standardized NIST FIS2 fingerprint matcher to the FVC2004 fingerprint database along with our as well as two other enhancements. The study confirms that the suggested enhancement robustifies feature detection, e.g. minutiae, which in turn improves the recognition (20% relative improvement in equal error rate on DB3 of FVC2004).

1 Introduction

Automatic fingerprint image enhancement plays a pivotal role in fingerprint recognition, since it strongly determines the success of all further steps. By succeeding the sensing stage and directly preceding feature extraction, the purpose of image enhancement is to facilitate the latter by "denoising" the signal. It has been shown previously that the quality of a fingerprint image directly affects the performance of a given recognition system [11, 12, 15]. In an ideal fingerprint image, ridges and valleys alternate and flow in a locally constant direction [16]. In realistic scenarios though, the quality of a fingerprint image may suffer from various impairments, caused by *i)* scares and cuts, *ii)* moist or dry skin, *iii)* sensor noise/blur, *iv)* wrong handling of the sensor (e.g. too low/high contact pressure), *v)* generally weak ridge-valley pattern of the given fingerprint, etc. While not acting against low quality fingerprints, methods to automatically assess the quality of a given impression, such as [7, 12, 19], are useful and complementary to this study.

The task of a fingerprint enhancement algorithm is to counteract the aforesaid quality impairments and to reconstruct the actual fingerprint pattern as true to the original as possible. Furthermore, unrecoverable areas should be labeled as such, since fingerprint enhancement at too noisy parts yields spurious information. There are several published studies on fingerprint image enhancement. Hong et al. [13] proposed an algorithm using Gabor band-pass filters tuned to the corresponding ridge frequency and orientation to remove undesired noise while preserving the true ridge-valley structures. Here, all operations are performed in the spatial domain, whereas the contextual filtering in [8, 17] is done in the Fourier domain. Either way, block-wise processing is used to obtain the enhancement result causing restoration discontinuities at block boundaries. These methods are likely successful in extreme bad quality regions, but also rather rigid under easy conditions. In [20, 22], the fingerprint's block-wise power spectra were multiplied by themselves but raised to the power of k, thus magnifying the dominant orientation. A block-wise Fourier transform is also employed by Chikkerur et al. [8, 9], followed by contextual filtering using raised cosines. In a related study [2], a standard discrete scale space has been used to contextually process fingerprints. To the contrast, we employ an efficient multigrid representation of a discrete differential scale space and follow a different enhancement strategy. For a more detailed review of fingerprint enhancement schemes we refer to [16].

In this study we propose the use of an image-scale pyramid and directional filtering in the spatial domain for fingerprint image enhancement. Image pyramids or multi-resolution processing is especially known from image compression and medical image processing [10, 14], but has not been utilized to enhance fingerprint images before. The Laplacian pyramid [1, 18] resembles bandpass filtering in the spatial domain. In this study, we decompose fingerprint images in a similar manner, since we expect all the relevant information to be concentrated within a few frequency bands.

Furthermore, we propose Gaussian directional filtering to enhance the ridge-valley pattern of a fingerprint image using computationally cheap 1D filtering on higher pyramid levels (lower resolution) only. The filtering directions are recovered from the orientations of the structure tensor [3] at the corresponding pyramid level. In contrast to other algorithms, no block-wise processing is performed, thereby avoiding block boundary artifacts.
In the following section, a detailed description of the proposed fingerprint enhancement algorithm is given. In section 3 we report on experiments performed on the FVC2004 database using the NIST FIS2 fingerprint matcher [21,23].

2 Fingerprint Image Enhancement

This section describes the proposed image enhancement for fingerprints and presents a comparative discussion with two other methods. The involved steps are arranged as illustrated in figure 1, each of them to be detailed below.

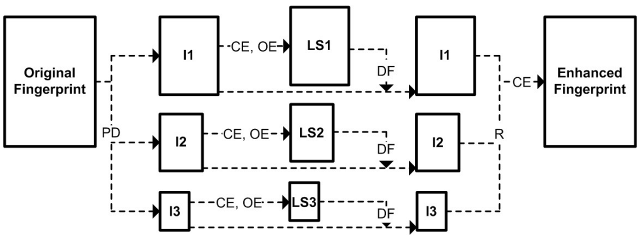

Figure 1. Data flow: Images (rectangles) and applied processing (connection labels).

2.1 Pyramid Decomposition (PD)

A pyramid decomposition requires resizing (scaling, or geometric transformation). To create our Gaussian and Laplacian-like pyramids, we define the $reduce\,(I, f)$ and $expand\,(I, f)$ operations, which decrease and increase an image I in size by the factor f, respectively. During *reduce*, the image is initially low-pass filtered to prevent aliasing using a Gaussian kernel. The latter's standard deviation depends on the resizing factor, which here follows the lower bound approximation of the corresponding ideal low-pass filter, $\sigma = \frac{0.75 \cdot f}{2}$ [3]. We initially reduce the original fingerprint image *fp* by a factor of $f_0 \geq 1.5$ in order to exclude the highest frequencies. In a further step we reduce the image size by a factor $f \leq 1.5$ for three times. This is also outlined to the left in table 1. To create images containing only band limited signals of the original image, we expand the three images g_{2-4} by factor f and subtract each

a) Pyramid Decomposition PD	
Gaussian-like	Laplacian-like
$g_1 = reduce\,(fp, f_0)\,;$	$l_1 = g_1 - expand\,(g_2, f)\,;$
$g_2 = reduce\,(g_1, f)\,;$	$l_2 = g_2 - expand\,(g_3, f)\,;$
$g_3 = reduce\,(g_2, f)\,;$	$l_3 = g_3 - expand\,(g_4, f)\,;$
$g_4 = reduce\,(g_3, f)\,;$	

b) Reconstruction R
$fp = expand\,(., f_0)\,;$
$expand\,(., f) + l_1$
$expand\,(l_3, f) + l_2$

Table 1. The pyramid building process.

of them from the next lower level, yielding l_{1-3}. The latter contain the adequately high, medium and low frequencies (ridge-valley pattern) of the original fingerprint. It is worth noting, that only the laplacian-like pyramid levels l_{1-3} are used subsequently in this study. In a further step, the contrast of the single band images is enhanced, following $l_i = CE\,(l_i)$ where $CE\,(x) = sign\,(x) \cdot \sqrt{|x|}$, to depreciate small vectors of x in comparison with those of large magnitudes. Note, that l_i contains no DC content, i.e. ridge pixels have negative values whereas valley pixels are positive (ideally). In figure 2, an example fingerprint beside its contrast enhanced pyramid levels l_{1-3} are displayed. The latter are used in an initial reconstruction step R as shown rightmost. This reconstruction is crude so far and represents only an isotropic (non-directional) enhancement, involving signal values starting at l_3 (see table 1). It is already visible that the portions of the fingerprint image that have been retained and contrast improved contain significant recognition information, whereas others containing high-frequency isotropic noise are attenuated.
Worth mentioning, we cover approximately half the bandwidth of the original image through the band-pass images in total, e.g. by setting f_0 and f to 1.5. This choice depends on the resolution of the fingerprint and normally can be approximated off-line, either experimentally or by using information on the used sensor. In the used images studied here the ridge frequency in a fingerprint image is ≈60 cycles per image width/height [6]. This translates to an image dimension of approximately 100-400 pixels for the method to be most effective.

2.2 Orientation Estimation (OE)

The ridge-valley orientation for each of l_{1-3} is estimated using the complex structure tensor approach [3]. The latter

Figure 2. i) Example fingerprint of the FVC2000-2 database, i-iv) its band-pass like decomposition via l_{1-3}, v) the "so-far" reconstructed fingerprint.

tensor is built as in equation 1

$$\begin{aligned} z_i &= \left[\left(D_x G(\sigma_1) + j D_y G(\sigma_1) \right) * l_i \right]^2 \\ &= C \cdot \left[\left(x \cdot G(\sigma_1) + j y \cdot G(\sigma_1) \right) * l_i \right]^2 \end{aligned} \tag{1}$$

where $G(\sigma_1) = exp\left(-\left(x^2+y^2\right)/\sigma_1^2\right)$, $j = \sqrt{-1}$, and "$*$" denotes a 2D convolution. As the equation shows, the operations $D_x l_i$ and $D_y l_i$ are realized by means of convolutions via $CxG(\sigma_1) * l_i$ and $CyG(\sigma_1) * l_i$ with C being the non-essential constant $-1/\sigma^2$. To obtain a robust estimation of the dominant direction (linear symmetry orientation) at a point, z_i is averaged using a Gaussian $G(\sigma_2)$, where $\sigma_2 > \sigma_1$ to yield the complex image *I20*. Likewise the magnitude of z_i is averaged to yield *I11*. To become independent of signal energy, we calculate $LS_i = \frac{I20}{I11}$ for level i, encoding local orientation ($\angle$) and symmetry strength ($||$). Also, by using *LS*, the magnitude of *I20* is attenuated if the underlying linear symmetry is not well-defined [4]. It is worth mentioning that all convolutions are separable and only 1D Gaussian (derivative) filters have been used. Furthermore, LS_1 is attenuated if its orientation deviates too much from the one of LS_2. This is done by $LS_1 = LS_1 \cdot |\cos(\angle LS_1 - \angle LS_2)|$. This is meaningful because LS_1 contains the most localized orientation (information also at minutia-level), but is also most susceptible to noise. In figure 3, LS_{1-3} for the example fingerprint are displayed using a HSV model, where its magnitudes modulate value V and the arguments (local orientation) steer hue H. When compared to a low-pass pyramid (e.g. Gaussian pyramid), the estimated orientation in band-pass pyramids (e.g. Laplacian pyramid) was found much more robust, in this context.

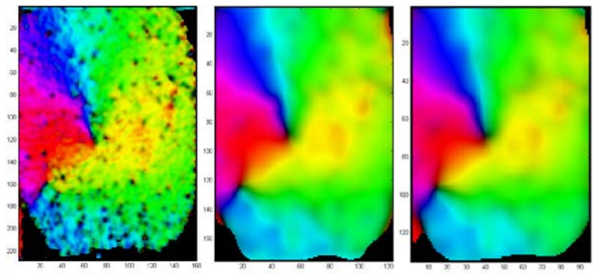

Figure 3. i-iii) HSV representation of LS_{1-3}, steering V (magnitudes) and H (arguments).

2.3 Directional Filtering (DF)

In order to enhance the SNR (signal-to-noise ratio), i.e. to remove sweat pores, scars, etc., we apply directional averaging to all levels l_{1-3}. The filtering direction within l_i is given by $\angle(LS_i)/2 - \pi/2$, thus it follows the ridges/valleys of the fingerprint. At every position, the neighboring pixels along a line are multiplied by a 1D Gaussian and summed to yield the new value. The possible different line directions are restricted (here 20). Furthermore, we also exploit the magnitude of LS_i: First, pixels where $|LS_i| < \tau_1$ are assigned to the background, i.e. they are set to 0 (effectively amounting to a segmentation of the fingerprint from the background or the heavily noisy regions). Second, only if $|LS_i| > \tau_2$ when measured on a small annulus centered at the current pixel, a reasonable quality (presence of ridge-valley pattern at level i) is ensured and the above filtering is done. Otherwise, the pixel is again set to 0. In this way, frequency selective structure tensors have helped to smoothen the image adaptively in the most appropriate direction per

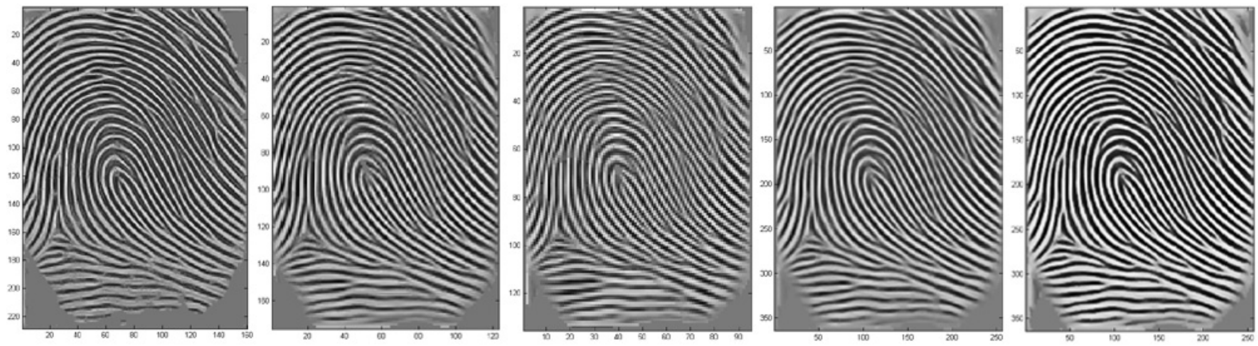

Figure 4. i-iii) Directional filtered l_{1-3}, iv) the reconstructed fingerprint, v) contrast enhancement.

layer. At the lowest level l_1, fine minutiae are preserved because the LS_1 filtering directions are sensitive to them. At higher levels l_{2-3} the rough ridge-valley flow is smoothed, and gaps are closed (e.g. caused by scars) because LS_{2-3} contain the global orientation. By use of the filtered levels l_{1-3} only, the image is reconstructed (R). A final contrast enhancement (CE) is done subsequently. In figure 4, the filtered versions of l_{1-3} for the example fingerprint are displayed, beside the reconstructed image and the final, contrast enhanced image. The 1D Gaussians used for this purpose are small and thus singular points like core and delta points do not need further attention. The resulting enhanced fingerprints exhibit a smooth ridge-valley flow, yet preserving the discriminative local and global information.

2.4 Qualitative comparison and discussion

Here, we present samples of enhancements to provide a visual feedback for a qualitative comparison between the proposed method and two other enhancement techniques studied by Hong et al. [13] and Chikkerur et al. [8], respectively. Implementations by the latter author, of both methods were used. Figure 5 depicts a fingerprint image from the FVC2004-1 database together with 3 enhanced versions as delivered by the mentioned techniques. The second image, corresponding to the output of Hong's method, is achieved by the use of Gabor-filters, tuned according to estimated frequency and the orientation within small blocks of the fingerprint. The filtering is only performed if the corresponding region exhibits ridge-valley structure that allows correct enhancement. The result of Chikkerur's method is visualized in the third image of figure 5. Here, all calculations are performed in the frequency domain, using STFT (Short Time Fourier Transform), involving small overlapping blocks. The ridge frequency and orientation are determined in the Fourier domain, to steer the contextual filtering by steep band-pass functions. The segmentation of a fingerprint is done by putting a pre-determined threshold to a block's energy. The final image in figure 5 depicts the result by the proposed method. As to be expected, our approach does not exhibit block-artifacts because the data processing is not block-wise. Qualitatively, it appears that our method produces high contrast between ridges and valleys and the result generally exhibits more fidelity to the original compared to the alternative approaches, because Hong's method appears somewhat more blurred while Chikkerur's approach has visible block-artifacts, especially near minutia points. Being the basic resource for most fingerprint recognition techniques, including semiautomatic forensics, it is to be expected that minituae neighbourhood degradation will decrease recognition performance. However, the validity of these qualitative observations need to be supported experimentally using publicly available databases and standard matching techniques, which we present next.

3 Experiments

In order to benchmark the capability of the proposed fingerprint enhancement algorithm, we need to test it on highly corrupted fingerprint data, where reliable enhancement becomes indispensable. Therefore we use the FVC2004 database [15], which was created to provide a tougher benchmark for state-of-the-art recognition systems than previous fingerprint verification competitions [6]. When collecting the fingerprint data, individuals were asked among other things to vary the contact pressure applied to the sensor and their fingers were additionally dried or moistened in order to enforce challenging image quality conditions. The test set of the FVC2004 consists of 4 databases, which were acquired using different sensor types and each of them contains 8 impressions of 100 fingers. Subsequently, we will refer to these databases as DB1-4. It is worth mentioning that DB4 was created using the SFinGE synthetic fingerprint generator [5] whereas DB1-3 are pop-

Figure 5. i) Example fingerprint of FVC2004-1, ii) enhancement by Hong, iii) Chikkerur, iv) proposed.

ulated by images representing authentic fingerprints sensed by real sensors. When carrying out fingerprint verification for a single DB, we follow the FVC protocol involving 2800 genuine trials and 4950 impostor trials.

First of all, we enhance all fingerprints of DB1-4 with three different enhancement methods: The proposed algorithm, and the methods of Hong and Chikkerur, which we already compared and inspected visually in section 2.4. Furthermore, we employ an independent fingerprint matcher (NIST FIS2 mindtct + bozorth3 packages [21, 23]) and take notes of the achieved EER (Equal Error Rate) per database and enhancement method. Ideally, all of the latter should lead to lower error rates for the fingerprint matcher, compared to when matching the original fingerprints. Table 2 shows

Enhancem. Method	DB1	DB2	DB3	DB4
no pre-enhancem.	14,5%	9,5%	6,2%	7,3%
Hong [13]	(16,9%)	14,4%	7,1%	9,8%
Chikkerur [8]	(19,1%)	11,9%	7,6%	10,9%
proposed method	12,0%	8,2%	5,0%	7,0%

Table 2. EER of the NIST FIS2 matcher on the original and pre-enhanced FVC2004.

the EER of the matcher on all 4 FVC2004 databases: The results in the first row were achieved when using no image enhancement at all. The other rows detail the matching performance if all impressions were initially enhanced by the method of Hong (second row), Chikkerur (third row), and by the proposed approach (last row). Surprisingly, we can observe that all enhancement methods but the proposed worsen (!) the error rate. Our approach clearly leads to the lowest EER on all 4 databases. Worth mentioning, no parameters of our enhancement method have been adapted to any of the used databases[1], neither were the others. Thus, the available fingerprint area after enhancement sometimes happened to be very small (especially in DB1). In figure 6 we show example fingerprints of DB1-4 next to their enhanced version, employing the proposed algorithm.

4 Conclusion

A novel image enhancement procedure for fingerprints has been presented. It is a continuous, (in the sense of not being block-wise), spatial domain approach. It does thereby not suffer from blocking artifacts. Both absolute frequency (isotropic information) and orientation (non-isotropic information) of the fingerprint pattern are utilized to obtain the enhancement. The former is implemented by exploiting several levels of a band-pass pyramid and treating them independently. The typical ridge-valley flow is coherence enhanced by using directional averaging and the structure tensor direction at each level. The approach is efficient because the main computations are done at at least 1.5 times lower resolution than that of the original, and by use of 1D filters only. The processing of the lowest level adds to the fidelity and details (conservation of minutiae) whereas the rough ridge-valley flow is cleaned and gaps are closed at higher levels. We have compared our approach to two other enhancement methods, qualitatively and quantitatively by use of a difficult fingerprint dataset. The results on the 4 FVC2004 databases are favorable to the suggested enhancement method. While the alternative techniques have been shown to improve the recognition performance in previous studies when processing fingerprints with more moderate noise than those affecting the FVC2004, the benefits of their enhancement apparently do not outweigh the introduced artifacts at presence of heavy but realistic sensing noise.

[1]Our algorithm was checked by inspection on selected fingerprints of DB2 from FVC2000 (compare figure 2-4)

Figure 6. One fingerprint of each DB of FVC2004 next to its enhanced version

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