Adaptive Processing of Latent Fingerprints

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Abstract- **In the paper is presented one new method for image quality enhancement of latent fingerprints. The aim is to equalize the uneven background and to improve the visual image quality, retaining the fingerprint minutiae. The processing comprises two main steps: 2D linear image filtration with sliding window, followed by image segmentation. The size of the filter window is relatively large and in result, the image background is suppressed but the sharp brightness transitions are retained. The image segmentation is based on the "triangle" algorithm, modified for this application. The quality of the binary image, obtained in result, facilitates the fingerprint matching.**

Keywords- **Fingerprints processing, background filtration, image segmentation**

I. Introduction

The matching of latent fingerprint images depends on their quality to a high degree. Various techniques had already been developed, comprising image histogram modification, image filtration, etc. [1, 2, 3]. The histogram modification is usually based on the famous algorithms for global or local histogram equalization, auto equalization, or contrast enhancement [4, 5, 6]. Most of the methods are aimed at the fingerprint itself, retaining or slightly changing the image background. Different filtrations are used as well, but in most cases the computational complexity is too high or some of the important features are lost in result of the processing [7]. The method "Wavelet Scalar Quantization" (WSQ), had been adopted by the Federal Bureau of Investigations (FBI) as its standard for fingerprint compression [8,9]. It involves the Discrete Wavelet Transform (DWT), adaptive scalar quantization of the wavelet coefficients and a two-pass Huffman coding. The computational complexity of the method is high and the compression is lossy.

The new approach, presented here, is aimed at the background equalization, retaining the most significant part of the processed image, i.e. the fingerprint. In result, the visual image quality is significantly improved, without affecting the fingerprint minutiae.

The paper is arranged as follows: Section II is focused on the algorithm for image background equalization; in Section III the principle of the algorithm for image segmentation is considered in detail; Section IV presents some of the experimental results obtained, and Section V is the conclusion.

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II. Background Equalization with 2D Linear Digital Filtration

The background equalization is necessary, because it makes easier the next operations – the detection and the segmentation of the fingerprint. For the processing is used 2D linear digital filter of non-recursive kind [10], modified for this application and presented by the relation:

$$\begin{aligned} z(i,j) &= g\,[\,x(i,j) - \frac{1}{L}\sum_{m=-N_1}^{N_1}\sum_{n=-N_2}^{N_2} x(i+m,j+n)\,] + \mu_x = \\ &= g\,[\,x(i,j) - \mu_x(i,j)\,] + \mu_x \end{aligned} \quad (1)$$

Here $x(i,j)$ is the brightness of the element (i,j) from the non-corrected image (before the uneven illumination correction); $z(i,j)$ – the brightness of the element (i,j) from the corrected image; μ_x - the mean brightness of the non-corrected image; $\mu_x(i,j)$ - the mean local brightness in the window around the pixel $x(i,j)$; $L=(2N_1+1)(2N_2+1)$ - the number of pixels in a rectangular window of size $(2N_1+1)\times(2N_2+1)$; g – coefficient, representing the contrast enhancement applied at the small details in the image ($g \geq 1$). The value of μ_x is defined by the relation:

$$\mu_x = \frac{1}{2}(x_{max} - x_{min}), \quad (2)$$

where x_{max} and x_{min} are correspondingly the pixels with maximum and minimum brightness value in the processed image.

The filtration, presented with Eq. (1) could be accelerated, transforming the processing in a recursive form, as follows:

$$\begin{aligned} \mu_x(i,j) &= \mu_x(i-1,j) + \mu_x(i,j-1) - \mu_x(i-1,j-1) \\ &+ \frac{1}{L}[\,x(i+N_1,j+N_2) - x(i+N_1,j-N_2-1) - \\ &- x(i-N_1-1,j+N_2) + x(i-N_1-1,j-N_2-1)]. \end{aligned} \quad (3)$$

Then, from Eqs. (1) and (3) follows:

$$\begin{aligned} z(i,j) &= z(i-1,j) + z(i,j-1) - z(i-1,j-1) + g\{\,x(i,j) - \\ &- x(i-1,j) - x(i,j-1) + x(i-1,j-1) - \\ &- \frac{1}{L}[\,x(i+N_1,j+N_2) - x(i-N_1-1,j+N_2) - \\ &- x(i+N_1,j-N_2-1) + x(i-N_1-1,j-N_2-1)]\}. \end{aligned} \quad (4)$$

The number of components in the last equation is always 11 and does not depend on the filter window size $(2N_1+1)\times(2N_2+1)$. In case that $N_1 >> 1$ and $N_2 >> 1$ the number of operations becomes:

$$\eta = \frac{1}{11}[(2N_1+1)(2N_2+1)+2] \approx 0.36.N_1.N_2. \quad (5)$$

For example, for $N_1 = N_2 = 63$ and using Eq. (5) is calculated $\eta \approx 1429$, i.e. the number of additions necessary for the recursive filter performance is more than 1400 times smaller.

For further simplification of the processing it is possible instead of applying one, two-dimensional filter to apply two, one-dimensional filters - the first one in the horizontal direction and the second one in the vertical direction, represented with the relations:

$$y(i,j) = g_1 [x(i,j) - \frac{1}{(2N_1+1)} \sum_{m=-N_1}^{N_1} x(i+m,j)] + \mu_x;$$
$$z(i,j) = g_2 [y(i,j) - \frac{1}{(2N_2+1)} \sum_{n=-N_2}^{N_2} y(i,j+n)] + \mu_y, \quad (6)$$

where $g = g_1 \times g_2$, and $y(i,j)$ is the pixel (i,j) of the image obtained in result of the first filtration (in horizontal direction), with mean brightness μ_x and $z(i,j)$ –the pixel (i,j) of the image obtained in result of the second filtration (in vertical direction), with mean brightness μ_y. By analogy with (4) the equations (6) are presented as follows:

$$y(i,j) = \\ = y(i-1,j) - \frac{g_1}{L_1}[x(i-N_1-1,j) - x(i+N_1,j)];$$
$$z(i,j) = \\ = z(i,j-1) - \frac{g_2}{L_2}[y(i,j-N_2-1) - y(i,j+N_2)], \quad (7)$$

where:

$$L = L_1 \times L_2; \;\; L_1 = 2N_1 + 1, \; L_2 = 2N_2 + 1 .$$

In result, the filtration is significantly accelerated because of the reduced number of performed operations:

$$\eta = \frac{2N_1+3}{3} + \frac{2N_2+3}{3} = \frac{2(N_1+N_2)+6}{3} = \\ = 0.66\,(N_1+N_2)+2. \quad (8)$$

If $N_1 = N_2 = 63$, then $\eta \approx 85$, i.e. in result of the recursive approach the number of additions is more than 80 times smaller. The algorithm efficiency is additionally enhanced in result of the double use of same filter.

The described filtration causes some distortions at the image edges. In order to avoid this, the matrix of the processed image should be artificially made larger [11] adding pixels in both directions (horizontal and vertical) and then the size of the original matrix $M_1 \times M_2$ becomes $(M_1 + 2N_1) \times (M_2 + 2N_2)$. The easiest way is to add zeros in both directions, but in result in the processed image are usually obtained some distortions, known as zero-padding artefacts. The better way is to use image replication of size equal with that of the filter window side.

The filter parameters N_1, N_2 and g_1, g_2 are defined in accordance with the uneven background illumination, which should be corrected.

III. IMAGE SEGMENTATION

In result of the background equalization the image histogram usually has only one maximum, which corresponds to the most frequent brightness value (the equalized image background) and the detection of a second maximum, which to point at the contours is not possible. For this reason, the segmentation is based on the so-called “triangle” algorithm [10], modified for this application. The presumption is that the contours are darker than the equalized background. The segmentation threshold is determined performing the following operations:

- Calculation of the image histogram $H(x)$ for $x = 0,1,..,Q-1$, where Q is the number of grey levels;
- In the image histogram $H(x)$, are defined 2 points:

  - First point (H_0,x_0) – corresponding to the histogram maximum, which is usually the mean value of the corrected uneven illumination;
  - Second point (H_1,x_1), defined by the relations:

$$H_1(x_1) = \psi H_0(x_0),$$
$$H_1(x_1) < H_0(x_0) \text{ for } x_1 < x_0. \quad (9)$$

The point (H_1,x_1) is placed in the part of the histogram, which corresponds to the objects, darker than the background. The value of the parameter ψ is usually set to be $\psi = 0.1$;

- The equation of the straight line, which connects the points (H_1,x_1) and (H_0,x_0) is defined by the well-known relation:

$$Ax + BH + C = 0, \quad (10)$$

where

$$x_1 \le x \le x_0,\; A = H_1 - H_0,$$
$$B = x_0 - x_1,\; C = H_0x_1 - H_1x_0, \quad (11)$$

- For each point of the histogram $H(x)$ is calculated the distance $D(x)$ to this line, in accordance with the relation:

$$D(x) = \frac{Ax + BH + C}{\sqrt{A^2 + B^2}}, \quad (12)$$

where A, B and C are defined by the straight line equation.

- The value θ of the variable x is defined, for which the distance $D(\theta)=max$. This value is the searched segmentation threshold, for which from Eq. 12 is obtained:

$$H(\theta+1) - H(\theta) \approx \frac{H_0 - H_1}{x_0 - x_1} \quad (13)$$

for the range $x_1 \le x \le x_0$.

The image is binarized, using the segmentation threshold θ for the separation of the objects, darker than the equalized background, in accordance with the relation:

$$p(i,j) = \begin{cases} 1, \text{ if } x(i,j) \le \theta_1; \\ 0, \text{ if } x(i,j) > \theta_1, \end{cases} \quad (14)$$

The binary image *p(i,j)* contains the detected and extracted contours.

IV. Experimental Results

The experiments were performed with specially developed software, implementing the presented algorithm. The test images (more than 400) were downloaded from a database accessed free via Internet. All images were greyscale, 8 bpp. For images in Figs.1 and 3 the window size of the filter for background equalization in horizontal and vertical direction was the same: 55 pixels; the filtration was performed consecutively in horizontal and vertical directions. After that, the image segmentation was performed in accordance with the algorithm, presented above. Some example test images are shown below.

Fig.1. Original test image (448 x 478 pixels, 8bpp)

Fig.2. The image from Fig. 1 after processing

Fig.3. Original test image (448 x 478 pixels, 8bpp)

Fig.4. The image from Fig. 2 after processing

Fig.5. Original test image (256 x 364 pixels, 8bpp)

Fig.6. The image from Fig. 5 after processing

The software implementation of the presented approach for processing of latent fingerprints proved its efficiency.

The results obtained after the processing of the test images from Figs. 1 and 3 are shown in Figs. 2 and 4 correspondingly. The visual quality of the images was enhanced, retaining the fingerprints minutiae. The filter retains the sharp transitions and in result even the sweat pores are retained (they are easily visible in Fig. 4). The image background is equalized and suppressed and this facilitates the matching process.

Special interest attracts the image from Fig. 5. In fact, there are two latent fingerprints on it (one of them – a little darker). The image size is 256 x 364 pixels. The filter window size is 311 pixels. This size is large enough to equalize the background, retaining the sharp brightness transitions in the processed image. In result of the processing the second fingerprint is significantly suppressed and the quality of the main one (which is supposed to be overlapped on the paler one) is enhanced. In the original image the brightness of the two fingerprints is almost equal and they are hardly distinguished. In result of the processing larger difference between the brightness of the two fingerprints is obtained and the main fingerprint is more evident. Together with this, the minutiae are retained – the ridges and sweat pores are enhanced and correspondingly, more explicit.

Similar results were obtained for low-contrast fingerprints: the original image, shown in Fig. 7 after processing with filter of size 511 pixels (in both directions) and image segmentation became as shown in Fig. 8. The image quality is enhanced, and some specific features (in this case – some small scars) became easily noticeable.

Fig.7. Original test image (256 x 364 pixels, 8bpp)

Fig.8. The image from Fig. 7 after processing

V. Conclusion

The presented investigation is focused on the quality enhancement of latent fingerprints. The aim was to suppress the image background and to enhance the fingerprint, retaining the sharp transitions (ridges, sweat pores, etc.). The use of relatively large filter of size, comparable or even larger than that of the processed image, suits this aim very well. The filtration is followed by image segmentation, based on the specially modified “triangle” algorithm. This algorithm was chosen because it corresponds with the statistics of the image, obtained in result of the preceding filtration. The experiments, involving large number of test images, proved the method efficiency. The presented results are comparable with results obtained with methods for fingerprint enhancement based on histogram modification [12], but the filtration is more efficient when complicated (for example, images containing more than one fingerprint) or low contrast images are processed.

The future work will be focused at investigations, which to permit the adaptive automatic selection of the most suitable processing, such as contrast enhancement and background equalization on the basis of the image analysis. For this will be used the image histogram, which to provide additional information concerning the needed contrast enhancement and image size analysis which to define the filter parameters.

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References

[1] A. Rowberg, B. Malcolm. Distortion-free Image Contrast Enhancement, “EuroPACS-MIR 2004 in the Enlarged Europe”, pp. 357-360.

[2] G. Sharma (Ed.). Digital Imaging Color Handbook, New York, CRC Press, 2003.

[3] Y. Kim. “Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization“. IEEE Trans. on CE, Vol. 43, No.1, 1997, pp.1-8.

[4] S. Bow. Pattern Recognition and Image Preprocessing, Marcel Dekker, 2002

[5] D. Fuentes, D. Mostefa, J. Kharroubi, S. Garcia-Salicetti, B. Dorizzi, G. Chollet. “Identity verification by fusion of biometric data“. Proceedings COST 275 Workshop on the Advent of Biometrics on the Internet, Nov. 2002, pp. 83–86.

[6] Al Bovik (Ed.). Handbook of Image and Video Processing. Academic Press, 2000.

[7] J. Yang, L. Lin, T. Jiang and Y. Fan. “A Modified Gabor Filter Design Method for Fingerprint Image Enhancement”, Pattern Recognition Letters, Vol. 24, 2003, pp. 1805-1817.

[8] International Standards Organization, ISO/IEC JRC1/SC37. Working draft, Biometric data interchange formats-Part 4: Finger image data, Geneva, Switzerland, 2004

[9] B. Sherlock, D. Monro. Optimized Wavelets for Fingerprint Compression, Proc. of IC on ASSP’1996.

[10] I. Young, J. Gerbrands, L. van Vliet. Image Processing Fundamentals. Delft, Netherland, 1996.

[11] R. Gonzalez, R. Woods. Digital Image Processing. Prentice Hall, 2002.

[12] R. Kountchev, Vl. Todorov, R. Kountcheva, M. Milanova. lossless Compression of Biometric Images and Digital Watermarking with IDP Decomposition. WSEAS Trans. on Signal Processing, Issue 5, Vol. 2, May 2006. pp. 684-691.