THE USV ANNALS OF ECONOMICS AND PUBLIC ADMINISTRATION | VOLUME 14, ISSUE 2(20), 2014

DEVELOPMENT OF OPTIMAL FILTERS OBTAINED THROUGH CONVOLUTION METHODS, USED FOR FINGERPRINT IMAGE ENHANCEMENT AND RESTORATION

Cătălin LUPU
"Ştefan cel Mare" University of Suceava, Romania
lupucata@yahoo.com

Abstract:
This article presents the development of optimal filters through covolution methods, necessary for restoring, correcting and improving fingerprints acquired from a sensor, able to provide the most ideal image in the output. After the image was binarized and equalized, Canny filter is applied in order to: eliminate the noise (filtering the image with a Gaussian filter), non-maxima suppression, module gradient adaptive binarization and extension edge points edges by hysteresis. The resulting image after applying Canny filter is not ideal. It is possible that the result will be an image with very fragmented edges and many pores in ridge. For the resulting image, a bank of convolution filters are applied one after another (Kirsch, Laplace, Roberts, Prewitt, Sobel, Frei-Chen, averaging convolution filter, circular convolution filter, lapacian convolution filter, gaussian convolution filter, LoG convolution filter, DoG, inverted filters, Wiener, the filter of "equalization of the power spectrum" (intermediary filter between the Wiener filter and the inverted filter), the geometrical average filter , etc.) with different features.

Key words: fingerprints; biometrics; Canny operator; filtering; edges detector; image processing

JEL classification: C63, C69

1. INTRODUCTION

A fundamental phase for the segmentation, for obtaining the characteristics of the elements and for the matching phase is the preprocessing phase. The preprocessing of the images consists of: the images enhancement; the images restoration; the highlighting of the features: edges and corners.

Image enhancement means increasing the image quality to a level that attenuates its interpretation or overdoing the existent characteristics of the image. The typical operations of the image enhancement: correcting the grey level (increasing the contrast); histogram equalizing; colors conversion; the noise smoothing; the features highlighting.

The image restoration means the retracing a degraded image by the faults from the acquisition system, knowing the nature of the faults. The degradation causes may be: faults of the lens of the eye or fingerprint over-taking sensor; nonlinearity of the sensor (which transforms the optic signal into electric signal); relative movement between the camera and the person; wrong focalization.

Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task. Moreover, observer-specific factors, such as the human visual system and the observer's experience, will introduce a great deal of subjectivity into the choice of image enhancement methods. There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided in to the following two categories: (i) Spatial Domain Methods and (ii) Frequency Domain Methods.

Digital image enhancement is one of the most important image' processing technology which is necessary to improve the visual appearance of the image or to provide a better transform representation for future automated image processing such as image analysis, detection, segmentation and recognition. Many images have very low dynamic range of the intensity values due to insufficient illumination and therefore need to be processed before being displayed.

2. SPATIAL DOMAIN METHODS

Large number of techniques have focused on the enhancement of gray level images in the spatial domain. These methods include histogram equalization, gamma correction, high pass filtering, low pass filtering, homomorphic filtering, etc.

In spatial domain techniques [14], we directly deal with the image pixels. In spatial domain for getting desired output the pixel vales are manipulated. Basically in spatial domain the value of pixel intensity are manipulated directly as equation (1):

$$G(x, y) = T\,[f(x, y)] \qquad (1)$$

Where f (x,y) is input image, G(x, y) is output image and T is an operator on f, defined over some neighborhood of f(x,y).

Understanding frequency domain concept is important, and leads to enhancement techniques that might not have been thought of by restricting attention to the spatial.

Y.-T. Kim [1] developed a method for contrast enhancement using brightness preserving bi-histogram equalization. Similar method for image contrast enhancement is developed by Y. W. Qian [2]. A block overlapped histogram equalization system for enhancing contrast of image is developed by T. K. Kim [3]. Other histogram based methods [4]-[6] etc. are also developed. V. Buzuloiu et al. [7] proposed an image adaptive neighborhood histogram equalization method, and S. K. Nike et al. [8] developed a hue preserving color image enhancement method without having gamut problem. Li Tao and V. K. Asari [9] presented an integrated neighborhood dependent approach for nonlinear enhancement (AINDANE) of color images. They applied the enhancement to the gray component of the original color image and obtained the output enhanced color image by linear color restoration process. In spatial domain techniques [16], we directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement.

3. FREQUENCY DOMAIN METHODS

In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image.

In the frequency domain the image enhancement can be done as shown in equation (2):

$$G(u,v)=H(u,v)F(u,v) \qquad (2)$$

Where G (u, v) is enhanced image, F (u, v) is input image and H (u, v) is transfer function.

1. Compute F (u, v), the DFT of input image.
2. Multiply F (u, v) by a filter function H (u, v) as G (u, v) = H (u. v) F (u, v).
3. Compute inverse DFT of the result by applying inverse Fourier transform.
4. Obtain real part of inverse DFT.

These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values.

A fundamental phase for the segmentation, for obtaining the characteristics of the elements and for the matching phase is the processing phase. The preprocessing of the images consists of: the images enhancement; the images restoration; the highlighting of the features: edges and corners.

In the following lines, we will emphasize the histogram equalizing and the noise elimination by building an optimal filter which, starting with the distorted image, will provide in the output an image, the closest possible to the ideal image [14].

3.1. HISTOGRAM EQUALIZATION (HE)

HE techniques are widely used in our daily life, such that in the field of consumer electronics, biometrics (fingerprint , eye, face, etc.), medical image processing, image matching and searching, speech recognition and texture synthesis because it has high efficiency and simplicity [10],[11],[12],[13]. The main idea of HE-based methods is to re-assign the intensity values of pixels to make the intensity distribution uniform to utmost extent.

To enhance an image, a brightness preserving Bi-HE (BBHE) method was proposed in [1]. The BBHE method decomposes the original image into two sub-images, by using the image mean gray level, and then applies the HE method on each of the sub images independently. At some extent BBHE preserves brightness of image.

Dualistic sub-image histogram equalization (DSIHE) [2] is similar to BBHE but DSIHE uses median value as separation intensity to divide the histogram into two sub-histogram. Minimum Mean Brightness Error Bi-HE (MMBEBHE) [4] is an extension of the BBHE method. In MMBEBHE the separation intensity is minimum mean brightness error between input image and output image. Recursive mean separate HE (RMSHE) [4] is an iterative technique of BBHE, instead of decomposing the image only once, the RMSHE method proposes for performing image decomposition recursively, up to a scalar r, generating 2^r sub-image. In RMSE, when r increases the brightness increase, but number of decomposed sub histogram is a power of two. Multi-histogram equalization (MHE) [10] overcomes the drawback of bi-HE, it decomposed the input image into several sub-image and then applying the classical HE process to each one.

Histogram equalization [14] has as a goal the image enhancement by eliminating the noise determinated by distortins provoqued by the fingerprint catching sensors or by the improper luminosity, obtaining an image of a superior quality. In order to compare some images for different illuminations, to discover some differences between them, we apply the histogram modification, bringing them to a standard value or we modify one of the histogram until it gets closer to the other one.

In order to enhance the image quality, by correcting some distortings or emphasizing some shapes, features, etc., we use some specific techniques, by theirown or in combination. The histogram equalizing algorithm used into practice is:

Step1. The image's histogram is calculated (where L=256 for an image with the dimension MxN)

```
For   i = 1,…, L executes
        h[i]=0
for I = 1,…,M
        for j = 1,…,N
                level=image[I,j]
                h[level] = h[level] + 1
```

Step2. The cumulative histogram of the image is calculated:

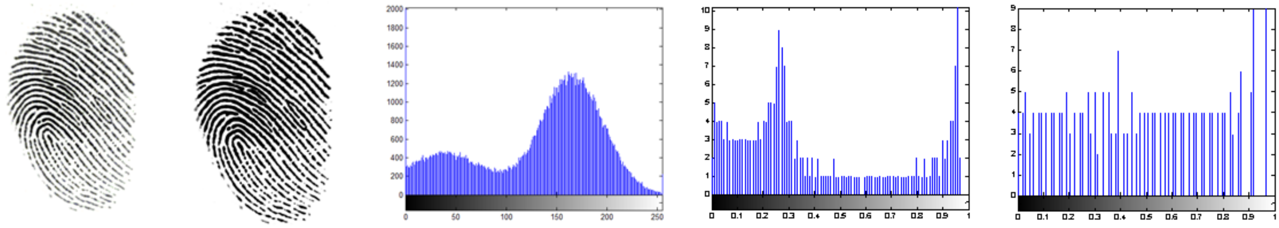
```
hc[1] = h[1]
for  I = 2,…,L executes
        hc[1] = hc[i-1] + hc[i]
```

Step 3. The new values of grey from the image are calculated, under the type of a transformation y = T(x) given by the formula:

$$y = T(x) = \left[\frac{hc[x] - hc[1]}{NM - hc[1]} (L-1) + 0.5 \right] \qquad (3)$$

```
For  i = 1,…,M executes
        old_levei = image [i,j]
        new_level = T (old_level)
        Image[i,j] = New_level
```

The test image is the fingerprint 101_1.tif of the database FVC 2004 and 001_1_1.tif ([15] – [16]) of the database CASIA. The images obtained after equalizing, with the afferent histograms are presented in figure 1.



a) b) c) d) e)

Figure 1. a) Test image fingerprint (101_1.tif) b). The image of the digital fingerprint after equalizing; c). The initial image histogram affected by the gaussian noise; d). The equalized histogram after cumulative sum;e). The normalized cumulative histogram

Source: a), b) – CASIA Database [15],[16]; c)-e) Own elaboration using MatLab

3.2. THE RESTORATION OF DEGRADATED IMAGES WITH DISTORTING FUNCTIONS INVARIABLE TO THE TRANSLATION, BY CONVOLUTION METHODS

Although very useful in several applications, they fail in some situations.

One method of filtering an image is to apply a convolution operation to the image to achieve: blurring, sharpenning, edge extraction or noise removal.

The restauration techniques of the images aims to build an optimal filter with a n×n kernel which by convolution with the initial image, affected by noise, can provide in the output an image the closest possible to the ideal one. To obtain this, it is used the linear filtering of the images in the frequency domain, which is based on the convolution between the image that is to be processed and a filtering kernel (Kirsch, Laplace, Roberts, Prewitt, Sobel, Frei-Chen, of mediation, circular (disk), lapacian, gaussian, LoG (Laplacian of Gaussian), DoG (Derivative of Gaussian), Wiener, the method of the inverted filter, etc.). There are more types of image transformations that produce representations in which appear unavailable properties in the image space. Thus, the Fourier transformation of an image is a representation in the frequency domain. More processings of the images suppose the elimination from the image of the components of a certain frequency, for instance those of low level or those of high level. These operations are easy to realise with the Fourier transformation of the images. The theory of the unitary transformations, show that such an operation (of convolution) is equivalent to a produce between the Fourier space of the image and the Fourier spectrum of the filtering nucleus; this is the convolution theorem.

4. METHODS TO DETECT THE EDGES BASED ON FILTERING FOLLOWED BY THE APPLICATION OF THE DIFFERENTIAL OPERATORS FOR THE DIGITAL FINGERPRINT

By detecting the edges we understand a technique that tries to identify the places with fast variations of the intesities. Each technique is characterized by a set of operators also called edges detectors.

The correct detecting of the edges is a very important problem in any biometrical system. The edges' processing system serves to simplify the images analysis by reducing considerably the data volume by restoring the structural useful information concerning the the images contours taken from the digital fingerprints. Most of the component modules of the biometrical systems depend directly or indirectly on the performances of the edges detector that is used.

According to the principle used for the detection of edges, they classify into:

- Methods based on applying the differential operators;
- Methods based on foltering followed by the application of the differential operators (Marr & Hildrith, Canny, etc.) ;

- Methods based on approximation on onedimensional surface having a profile similar to the edge;
- The residues method;
- Methods that work with discreet surfaces, using the direct approximation of the differential operators by finite differences;
- Methods that work with approximated surfaces by a continual function and which use the analytical form of the differential operators.

The detecting techniques of the edges have two different steps:

- Marking all the points characterized by fast variations of the intensities
- Selecting the edge points.

4.1. THE CANNY OPERATOR

The Canny operator ([22], [23]) enhances the images from the following points of view:

- The detecting itself of the edge (reducing the error rate – the detector does not lose the frontier points and it does not respond to the points that are not frontier points);
- The localisation accuracy (the frontier points are well located – the distance between the frontier points found by the detector and the real ones must be minimum);
- The answer uniqueness (the detector provides only one answer to only one frontier point).

The Canny algorithm consists in the following steps:

Step 1:

It is applied the Gaussian filter.

The bigger the width of the mask is, the smaller the detector sensitivity to the noise is.

Step 2:

The Sobel operator is applied to the image resulted from the step1, obtaining the matrix of the gradient amplitudes. D(x,y) = |Dx| + |Dy| (the gradient is approximated by the image convolution with the following masks:

-1	0	+1
-2	0	+2
-1	0	+1

Dx

+1	+2	+1
0	0	0
-1	-2	-1

Dy

Figure 2. Convolution masks for Sobel operator

Source: Canny Edge Detection Tutorial, [24]

Step 3:

It is calculated the gradient direction in each point, obtaining the directions matrix:

θ (x,y) = arctg (Dy / Dx)

Step 4:

It is adjusted θ to one of the directions from the discreet space of the images, more precisely the one which is the closest to the θ.

Step 5 (non-maxima suppression):

The Sobel detector , like all the detectors based on convolution masks, produces more front points for the same frontier point (more masks can contain one frontier point). That's why, the amplitudes matrix can contain wide areas around the frontier. In this step are eliminated the pixels which do not have the maximum amplitude locally (in the environs of a pixel).

Frontier points are declared those points whose amplitude is maximum locally on the gradient direction. The other points are eliminated (set at zero).

For each C pixel
Considering A and B the pixels from C environs on the C gradient direction
If D(A) > D(C) or D(B) > D(C) then D(C) = 0

The effect of this step is thinning the frontier without interrupting it. We will note with 15 the amplitudes matrix rsulted from this step.

Step 6 (hysteresis thresholding):

In this step the false frontier pixels (the noise) are eliminated without interrupting the frontier (contour). For this, we use the "histerezis"operation, which consists of applying two thresholds: the low threshold, TI and the up threshold, T2 (T1 approximately equal to 2*T1). These threshols are applied separately to the image resulted from the previouos step, I5 resulting 2 binary images, T1 and T2. In T1 they have a value of 1 pixel with the amplitude >T1 and in T2 they have the amplitude >T2.

The image from T2 has interruptions in the frontier but contains less false points.

The points from T2 are connected in the contours

The tracing of a frontier begins with a point from T2. Points from T2 are connected until it is reached a pixel p which cannot be connected with another point from T2 (it does not have neighbors in T2 on no one of the 2 4 directions). In this moment, within T1, in the environs of 8 pixels of the pixel p, is searched a pixel that can be connected to the contour. It is connected to the frontier points from T1 until we reach to a pixel with a value different from zero in T2 (or we reach to the end of the contour). In this way, we fill in the frontier interruptions from T2 with pixels from T1.

The images obtained after applying the Canny filters, image after smooting and image thinning are presented in figure 3.

a) b) c)

Figure 3. a) The image obtained after applying the Canny filters; b) image after smooting (filling gaps); c) image after thinning

Source: Own work using MatLab software

4.2. CONVOLUTION FILTERS

The image enhancement techniques are used to refine a given image, in such a way that certain particularities of the image would become more visible or could be detected by the systems of automatic analysis of the images. By enhancing the image, we can notice details that weren't easily noticeable in the initial image (for instance the initial image has too much noise or an deficient contrast).

Very often, it is possible that after applying the algorithms of „image enhancement" to appear undesirable effects, too. The important information that apperade in the initial image can be lost or the enhanced image can turn out to be weaker qualitatively than the initial image. More than that, it is obvious that the enhancement algorithms cannot produce information that don't appear in the input image.

We will present a method of image enhancement, more precisely: the noise reduction

The noise from teh digital images can be produced by a multitude of sources. The acquisition process of the digital images, that transforms an optical image into a continual electrical signal is a primary process that generates noise. In each step from the acquisition process there are fluctuations caused by natural phenomena and these ones add an aleatory value to the extraction of each value of the luminosity for a given pixel.

There are two types of pixels:

- Independent of the image content;
- Dependent of the image content.

An image with a noise independent of the image content can be shaped by: g(x,y) = f(x,y) + n(x,y), where f(x,y) is the input image for the image formation device (real image) and n(x,y) represents the noise independent of the image content, also called additiv noise.

If the noise depends on the image content (for instance, monochromatic radiations produced by a surface, that produce wave interferences), the noise can be represented by an unlinear model. Because these mathematical models are more complicated, the noise is considered, if possible, as being independent of the dates (the image content).

The mathematical shaping of the noise is useful not only for their reduction but also for the synthesis of some images with typical noise, with the aim to analyse the algorithms of noise filtering.

There is a series of modalities to eliminate the noise:

- By average filter: the average filtering can be obtained by applying a convolution mask with the dimensions (2K+1 X 2L+1), each coefficient having an equal value with the opposite of the total number of coefficients from the kernel. The noise reduction is more significant, the bigger the kernel dimension is [17],[19];
- By median filter: this type of filtering does not use convolution masks to obtain filtered images. For each pixel form the input image (m, n) the filtering window is centered and it is calculated the average of the pixels value found within the window, this value becoming the pixel (m, n) from the resulted image. This filter reduces the variation of the intensities from the image, producing regions of constant intensity or almost constant [17],[18];
- By the images average: using this type of noise reduction starts from three basic assumptions:
  - That relatively a big number of input images are available;
  - That each input image was affected by the same additive noise;
  - That the additive noise appears aleatory, it has the 0 average and it is independent of the image [17] - [19].
- By Gaussian filter: it uses nucleus that represent approximations of the Gauss surface. The operator consists of combining the derivate of two bidimensional images and the filtering to reduce the noise using a Gaussian filter goes down.

Advantages of Gaussian filtering [17], [19], [20]:

- rotationally symmetric (for large filters) ;
- filter weights decrease monotonically from central peak, giving most weight to central pixels;
- Simple and intuitive relationship between size of σ and the smoothing;
- The Gaussian is separable.

Advantage of seperability:

- First convolve the image with a one dimensional horizontal filter;
- Then convolve the result of the first convolution with a one dimensional vertical filter;
- For a k×k Gaussian filter, 2D convolution requires k^2 operations per pixel;
- But by using the separable filters, we reduce this to 2k operations per pixel;
- Convolution of a Gaussian with itself is another Gaussian , so we can first smooth an image with a small Gaussian. Then, we convolve that smoothed image with another small Gaussian and the result is equivalent to smoothing the original image with a larger Gaussian. If we smooth an image with a Gaussian having so σ twice, then we get the same result as smoothing the image with a Gaussian having standard deviation (2σ).

For the Sobel filter are realised two convolutions with nucleus form the relation (6). The result of the Sobel operator represents the sum or the maximum of the two convolutions. The first nucleus is used for the horizontal edges, and the second one for the vertical ones. Each nucleus corresponds to a derivation on a perpendicular direction on the edge direction. In the same time the Sobel filter has also an effect of noise reduction (in a certain measure) [18], [20].

4.3. CONVOLUTION OPERATORS

The intensity modifications and dicontinuities (amplitude) of an image (digital fingerprint or eye) constitue fundamental features that can indicate objects in the image. These discontinuities are called contours. The application of the convolution operators [21], with their masks, is useful for the processing phase of the images (improvement and restauration of the images). For all the operators below, the intensities are replaced with the sums obtained by the images convolution [21] with the appropriate masks.

a) Kirsch operator:

$$H_1 = \begin{bmatrix} 1 \\ -1 \end{bmatrix},\ H_2 = \begin{bmatrix} 1 & -1 \end{bmatrix},\ H_3 = \begin{bmatrix} 1 & 0 & -1 \end{bmatrix} \tag{4}$$

Where H_1 is used to detect the horizontal contours while the masks H_2 and H_3 are used for the vertical contours of the image.

$$H_1 = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \quad H_2 = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \quad H_3 = \begin{bmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & -1 & 0 \end{bmatrix} \quad H_4 = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{bmatrix} \tag{5}$$

$$G = \max \{ \text{sum}(H_1), \text{sum}(H_2), \text{sum}(H_3), \text{sum}(H_4) \} \tag{6}$$

Advantages: used to detect the edges by calcuating the magnitude of the gradients that have high grades, using eight compass masks on the directions N, NV, V, SV, S, SE, E and NE.

Disavantages: It needs more time to calculate the magnitude using the eight masks and it does not respond better than the Sobel and Prewitt operators.

b) Laplace operator:

$$H_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}, H_2 = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \tag{7}$$

where H_2 is the Laplace operator proposed by Prewitt.

Advantages:

It aproximates the derivatives of the function of the image by differences, calculating the edges magnitudes, using one convolution mask;

It is invariable to the rotation, having the same properties in all directions;

Disadvantages: it can respond in a double way to certain contours in the image**.**

c) Roberts operator:

$$P = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \tag{8}$$

$$R=K\sqrt{sum(P)^2 + sum(Q)^2} \text{ for instance k=7} \tag{9}$$

Advantages: the main advantage of this detector is the simplicity of the calculations: addition and deduction operations with values of only 4 pixels.

Disadvantages: because it uses a very small nucleus, it is very sensitive to noise. Also, its response to the real frontiers is weak if these do not have a very high intensity.

d) Prewitt operator:

$$P=\begin{bmatrix}1 & 1 & 1\\ 0 & 0 & 0\\ -1 & -1 & -1\end{bmatrix},\ Q=\begin{bmatrix}0 & 1 & 1\\ -1 & 0 & 1\\ -1 & -1 & 0\end{bmatrix},\ \ R=\begin{bmatrix}-1 & 1 & 1\\ -1 & 0 & 1\\ -1 & 0 & 1\end{bmatrix} \tag{10}$$

Prewitt operator resembles to the Sobel operator described below.

e) Sobel operator [11]:

$$P=\begin{bmatrix}-1 & -2 & -1\\ 0 & 0 & 0\\ 1 & 2 & 1\end{bmatrix},Q=\begin{bmatrix}-1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{bmatrix} \tag{11}$$

$$R=\sqrt{sum(P)^2+sum(Q)^2} \tag{12}$$

Advantages: Sobel operator solicitates more calculations than Roberts operator, but its mask of convolution being bigger, it flattens more the image and for this reason it is less sensitive to noise.

Examples of Sobel convolution filters applied to the digital fingerprint(after the x direction, after the y direction and after xy direction) are presented in figure 4.

a) b) c)

Figure 3. Application of the Sobel operator on x direction, on y direction and on xy direction for the test image in figure 1

Source: Own work using MatLab software

After the convolution between the nucleus and the given image is realised, we obtain a new improved image.

4.4. CORRELATION BETWEEN TWO SIGNALS

It is realised the correlation between the new and the old image.

The correlation coefficient is a metric that expresses the similitude (the matching level) between two signals, that’s why , it is very often used to search template matchings. The correlation coefficient r of the pair (x, y) is calculated using the following formula:

$$r_{xy} = \frac{\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \cdot \frac{\sum_{i=1}^{n} y_i}{n}}{\sqrt{\left(\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}\right) \cdot \left(\sum_{i=1}^{n} y_i^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}\right)}} \quad (13)$$

The automatic correlation of the images [8] – is realised by establishing a geometrical relation between the two images. The optimal method of automatic correlation of the images is chosen depending on type of the parameters of the convolution filters, on the informative content and on the rapport signal/noise.

The correlation methods are:

- The method of sequential detecting of the similarity ;
- The method of bidimensional correlation;
- The method of one dimension correlation;
- The VLL method;
- The method of the images correlation by identifying the features (it involves reducing the initial dimension of the images by creating image pyramids and then identifying the corresponding points at the highest level of the pyramids) .

The coefficient between two image segments is determined with the formula:

$$c = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(A_{ij} - \overline{A}\right)\left(B_{ij} - \overline{B}\right)\right]}{\sqrt{\left[\sum_{i-1}^{m}\sum_{j=1}^{n}\left(A_{ij} - \overline{A}\right)^2\right]\left[\sum_{i-1}^{m}\sum_{j=1}^{n}\left(B_{ij} - \overline{B}\right)^2\right]}} \quad (14)$$

where:

c = the correlation coefficient between the two segments;

m= the line number;

n= the column number;

A_{ij}, B_{ij} = the value of grey of the point placed on the i line, column j, from segment A, respectively B

$\overline{A}, \overline{B}$ = the average of the grey values from the segment A, respectively B.

5. CONCLUSIONS

All the methods presented in this paper refer to the restoration of the degradated images with invariable distorting functions during the translation, using convolution methods. The optimal filter was obtained by applying the convolution filters with different features that, going from the initial image and applying to it different convolution filters, can provide in the output an image the closest possible to the ideal one.

The authors have used MatLab software in order to simulate the preseted methods. This software is suitable for image processing tasks, also providing specific functions for image processing and restoration. The main contribution is that the authors have used different filters and operators in order to enhance and restoration of degraded fingerprint images taken from a sensor.

ACKNOWLEDGMENT

This paper was supported by the project "Sustainable performance in doctoral and post-doctoral research - PERFORM - Contract no. POSDRU/159/1.5/S/138963", project co-funded from European Social Fund through Sectorial Operational Program Human Resources 2007-2013.

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