Optik 127 (2016) 1251–1259

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

A new approach for the detection of mammary calcifications by using the white Top-Hat transform and thresholding of Otsu

Mohamed Amine Guerroudji*, Zohra Ameur

Laboratory analysis and modeling phenomena random (LAMPA), University of Tizi-Ouzou, Tizi Ouzou, Algeria

ARTICLE INFO

Article history:
Received 9 February 2015
Accepted 30 October 2015

Keywords:
Calcification
Mammography
Top-Hat transform
Gaussian filters
segmentation
Otsu

ABSTRACT

The mammography is the technique of imagery the most used to detect tumors at an early stage, it is currently the principal investigation in the tracking of the breast cancer. The presence of calcification in mammography is particularly interesting for the early detection of the breast cancer. In this paper, we propose to use a system for the detection of calcifications, based on a new approach suggested of pretreatment of image mammography. The latter is based on the suppression of noise (to decrease the noise to the maximum) by a Gaussian filter in order to bring out all the spots (Clear Spots) possible to be calcifications; by using an operator of the white Top-Hat transform. This hat is resulting from the mathematical morphology, which makes it possible to keep only these small structures. The segmentation by the simple technique of Otsu [1] is then used in order to separate detected calcifications. Visually, the obtained results are very clear, and show the good performance of the new approach suggested in this work. This latter allows extracting successfully the calcifications starting from the mammography referents from the mini-MIAS database [2].

1. Introduction

Research in medical imagery is one of the most active disciplines of the image processing. These recent discovery allows not only a better diagnosis but also offers new hopes of treatment for many diseases (like the breast cancer). Indeed, the breast cancer constitutes the most common cause of death women [3]. Particularly in Algeria, every year about 10,000 new cases are detected mostly in the 40 s (forties). 95% of the cases arise at an advanced stage of pathology [4]. The stage of the diagnosis is a key stage in the struggle against the breast cancer as for any other pathology. Consequently, the detection of cancer, the analysis and the treatment of cancer became a major research orientation. The modern imagery technology has already had on the rescue early cancer detection capacity, and more precisely, the diagnosis of the disease. For this reason, the radiological technique the most effective is mammography [5–7]; particularly, lesions on the level of the breast. According to the radiologists an important indicator of the breast cancer is the presence of calcifications which appear in 30% to 50% of the cases diagnosed by mammography [8–11]. The mammography is a technique with low dose of X-rays that does not allow a good visualization of the internal structure of the breast. These difficulties and the low quality of mammographic images are making that analysis is particularly tiring and wasting time. Consequently, the design of a system of computer-aided detection (CAD) represents a system to help the radiologists in the interpretation of the mammography for the tracking of mass and calcification [12]. In spite of efforts made by the researchers, the automation of detection of mammary pathologies remains always difficult. During last years, there were significant efforts in the development of algorithms for the detection of calcifications in the images of mammography. Among the method the most important are those which use the representation of mammography based on the improvement of contrast and the detection of calcifications by the Top-Hat transform morphological [3,11,13,14]. Other improvements of contrast based on the Top-Hat transform but they are applied to different types from the images to levels of gray [15,16]. This last provides tools for the extraction of calcifications even if calcifications are located on a non-uniform background. Other studies have been conducted on mammography image for the local contrast enhancement [17,18] and the noise equalization [19], these latter are very important process in the stage of pretreatment of the images to increase contrast between the clear and dark zones to reveal the characteristics of the limits, the main aim of clearness of the image is to highlight fine details. There is also a method based on the wavelet transform to detect the calcifications gathered in mammography [20–24]. This transform offer a method of a very

* Corresponding author. Tel.: +213 669 56 91 63; fax: +213 552 95 86 30.
E-mail addresses: ma.guerroudji@yahoo.com (M.A. Guerroudji), ameurzohra@yahoo.com (Z. Ameur).

http://dx.doi.org/10.1016/j.ijleo.2015.10.192
0030-4026/

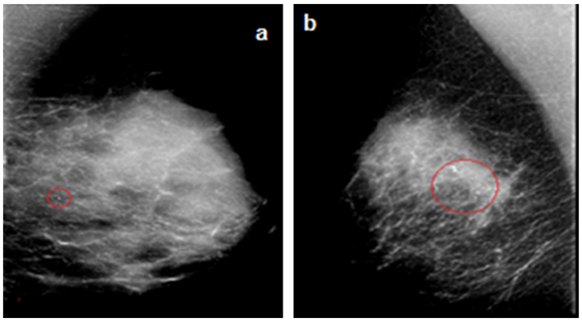

Fig. 1. Examples of mammography: (a) red circle indicates the macro-calcifications zone; (b) red circle indicates the micro-calcifications zone. (For interpretation of the references to color in figure legend, the reader is referred to the web version of the article.)

sparse and effective representation for the mammography, and it is regarded as being a mixture of several basic functions obtained by contractions, dilations and translations from the mother wavelet.

In this paper, a prototype of a system of detection of mammary pathologies, in particular calcifications, was put in work. For this reason, we propose a new approach to improve the detection of calcifications in the digitized mammography. This approach is based on two principal stages, suppression of the noise by the filter Gaussian and the improvement of contrast between calcifications and the background digitized mammography. We will make an effort in the improvement of contrast by the operations of the mathematical morphology (by using a morphological transformation White Top-Hat), which was used like a first stage of image processing. In the second phase, we use a segmentation of the area of interest for the identification of calcifications, based on the threshold of Otsu [1]. The method suggested has been tested on several images from the mini-MIAS database of mammograms [2], noting that the obtained results validate the superiority of our proposed approach.

The rest of this paper is structured as follows: Section 2 briefly presents basic information on calcifications in the mammography image. Section 3, we present our approach of detection of calcification by the improvement of contrast. Section 4 presents a very simple method for the segmentation of calcifications. The obtained experimental results are presented in Section 5. Finally, our conclusions are presented in the last section.

2. Basic information on calcifications

The presence of calcifications which generally seem luminous spots in mammary tissue, are tiny calcium deposits [25,26]. It is usual to distinguish two great types of calcifications according to the size: macro-calcifications and micro-calcifications [25,26]. The sizes of micro-calcifications (Fig. 1a) are in the range of 0.1–1.0 mm with an average diameter of approximately 0.5 mm [26]. Once their size exceeds 1.0 mm, they are macro-calcifications (Fig. 1b) [10], these last, are often benign whereas micro-calcifications require more attention. The luminous spots in the mammography with a diameter lower than 0.1 mm are considered as a noise of high frequency [10].

3. Detection method

This section presents the procedure of detection that is used in this work. It is summarized in Section 3.1 and the detail of each stage of this proposal is explained in the following sections.

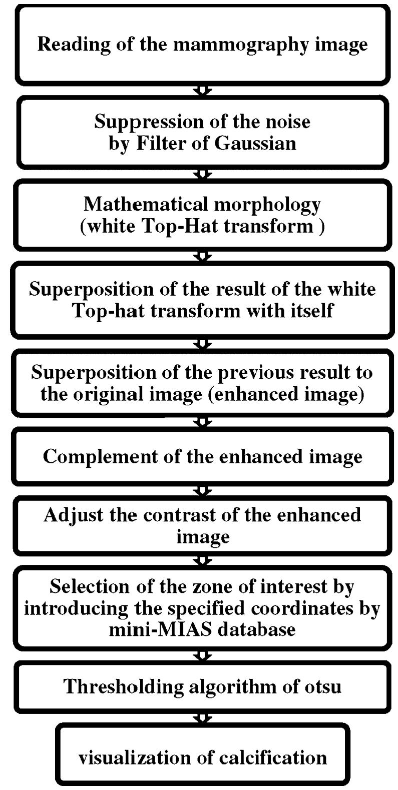

Fig. 2. Diagram of the proposed algorithm for the detection of calcifications.

3.1. *The proposed Algorithm for the detection of calcifications*

The diagram presented in Fig. 2 summarizes the several stages that we have proposed in our approach for detecting the calcifications.

3.2. *Pretreatments*

In spite of effort made by the researchers, the automation of the mammary pathologies detection remains always difficult. In this work, we propose a digital technique of pretreatment of the image based on the three following stages:

3.2.1. *Stage (1): noise suppression*

As calcifications are spots of small size and often of low intensity, designing a filter which is able to distinguish them from noise is very difficult. We call this initial filtering smoothing “fine”, simply because it modifies a little bit the information that we are seeking to locate.

We consider the Gaussian distribution that is given by the following expression:

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{\frac{(x-\mu_1)^2+(y-\mu_2)^2}{2\sigma^2}} \quad (1)$$

with σ is the standard deviation and μ is the average.

Gaussian filtering uses this distribution to define a convolution filter. As we work on the discrete images, we propose to use a discrete approximation of the Gaussian distribution in a finished filter of convolution.

In this case, we considered a Gaussian filter of standard deviation of $\sigma = 0.5$ to reduce the noise present in the image mammography (see Fig. 3a) and to keep only the significant peaks. The resulting image is presented in Fig. 3b.

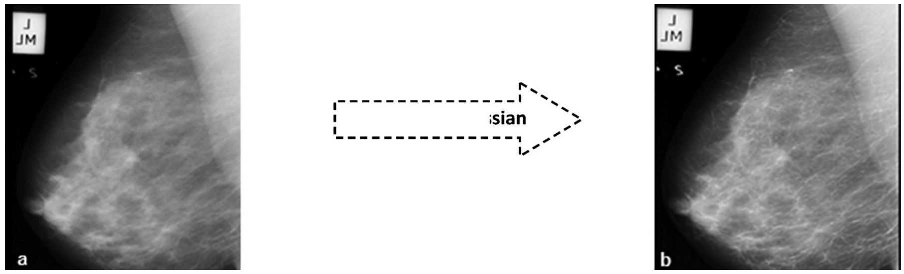

Fig. 3. Noise suppression: (a) original image; (b) filtered image.

3.2.2. *Stage (2): mathematical morphology*

Mathematical morphology is a science of the form and structure. The basic principle of mathematical morphology is to compare the objects which we want to analyze with another object of reference, in size and in a known form, called structuring element. To some extent, each structuring element revealed the object in a new form. The fundamental operations of mathematical morphological are erosion and dilation [15,16,27–29]. f is an image in levels of gray and E is a structuring element. Dilation and erosion of $f(X)$ from (y), noted $f \oplus E$ and $f\Theta E$, are defined respectively as follows,

$$f \oplus E = \max_{u,v}(f(i-u, j-v) + E(u, v)) \tag{2}$$

$$f\Theta E = \min_{u,v}(f(i+u, j+v) - E(u, v)) \tag{3}$$

with $f(X)$ is the corresponding to the small clear zones of the image, x is the $x(i,j)$ is a point of an image, $E(y)$ is the structuring element and y is the $y(u,v)$ are the sizes of the structuring element E.

Based on dilation and erosion, the opening and closing $f(x)$ from $E(y)$, noting that $f \bigcirc E$ and $f \bullet E$, are defined respectively as follows,

$$f \bigcirc E = (f\Theta E) \oplus E. \tag{4}$$

$$f \bullet E = (f \oplus E)E. \tag{5}$$

The detection of small target lesion was done according to the operator of the Top-Hat transform resulting from the mathematical morphology [15,27,28,30,32], which makes it possible to keep only these small structures. In this paper we adapted this technique to use it for the detection of calcification, in other words we propose a technique of improvement of the image mammography for the detection of calcifications by using the white Top-Hat transform. By carrying out the difference, between the initial image and its opening $f \bigcirc E(x)$ and by a structuring element E of size y, $E(y)$, we extract the peaks of which the thickness is lower than y.

$$\mathrm{WTH}(x) = f(x) - f \bigcirc E(x) \tag{6}$$

3.2.3. *Stage (3): contrast enhancement*

After the white Top-Hat transform, a contrast enhancement is carried out to highlight all the spots of high frequency, in other words, all regions likely to beings calcifications. That is why we are improving the images on three stages that are described as follow:

- A superposition of the result white Top-Hat transform with itself.
- A superposition of the previous result to the original image (enhanced image).
- Adjust the contrast of the enhanced image, specifying contrast limits between [0.39 1].

By applying these stages to images mammography with a choice of the structuring element used for the Top-Hat transform corresponding to a disk [31,33] with a size of 5 × 5 (it is the mean size, of a basic element of a calcification), we obtained the following results (see Fig. 4).

The complement of enhanced image makes it possible to accentuate the presence of calcifications. The thresholding will extract only these microstructures. Fig. 5 presents a comparison between complement of the image before and after the pretreatment.

Noting that, this study confirms the performance of the image mammography improvement by the white Top-Hat transform for the detection of calcifications.

4. Segmentation method

Segmentation method is regarded as the method of reference in the field of the thresholding of histogram [34]. These methods are largely used in image segmentation mammography [6], in order to detect the zones of tumor or calcifications. In this paper, we chose a simple segmentation by the Thresholding of Otsu [1]. The principle of this method consists in separating the pixels of an image in two classes c_1 (background), c_2 (object) starting from a threshold S (see Fig. 6) [1,20,35,36]. The class "background" gathers all the pixels having a level of gray lower than the threshold S whereas the

Table 1
The mini-MIAS images used in the proposed CAD system.

	Risk	No. of images in mini-MIAS	Images used in the proposed CAD system
Calcification	Benign	13	mdb 218, 219, 222, 223(2), 226(3), 227, 236, 240, 248, 252
	Malignant	12	mdb 209, 211, 213, 231, 238, 239(2), 241, 249(2), 253, 256

Table 2
The information annotated by the radiologist [2].

	mdb 219	mdb 209	mdb 226	mdb 252	mdb 253	mdb 256
The severity of the abnormality	Benign calcification	Malignant calcification	Benign calcification	Benign calcification	Malignant calcification	Malignant calcification
The coordinates of calcification (in pixels)	x = 546 y = 756 R = 29	x = 647 y = 503 R = 87	x = 329 y = 550 R = 25	x = 439 y = 367 R = 23	x = 733 y = 564 R = 28	x = 400 y = 484 R = 37

Mammography Image with Suppression of the noise by Filter of Gaussian	Superposition of the result of the white Top-Hat transform with itself	enhanced image	Adjust the contrast of the enhanced image

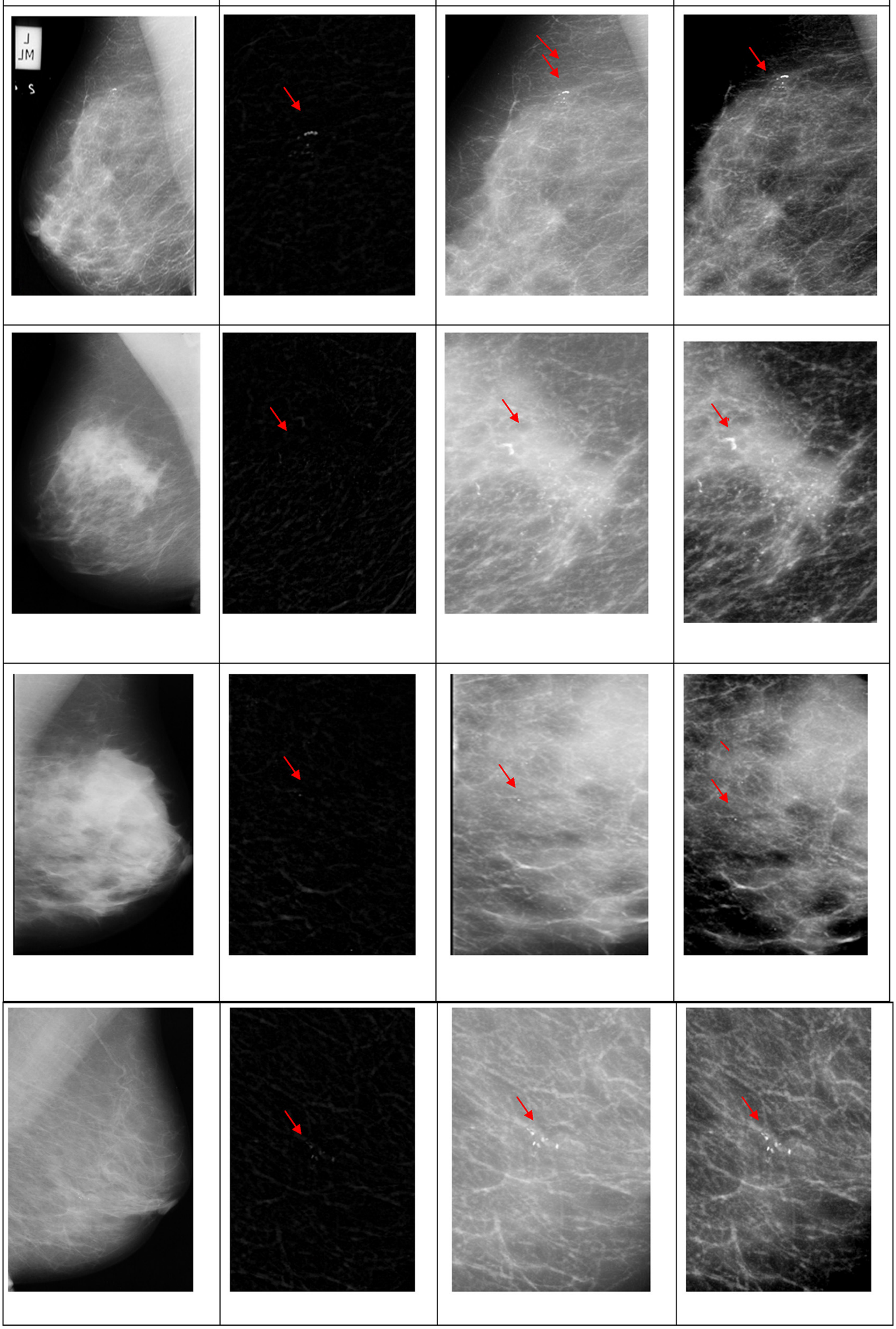

Fig. 4. Images treated by white Top-Hat transform.

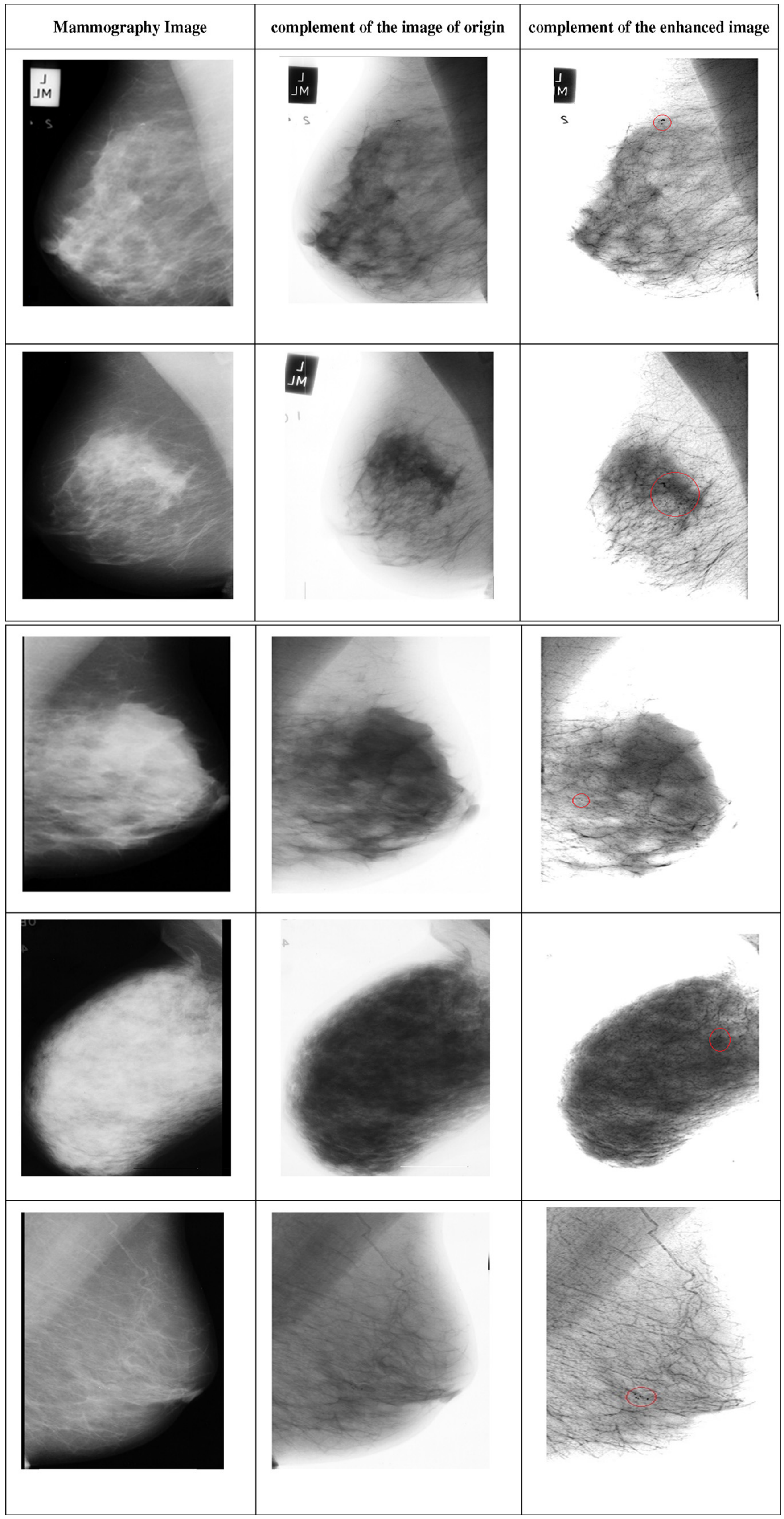

Fig. 5. Complement of the enhanced image.

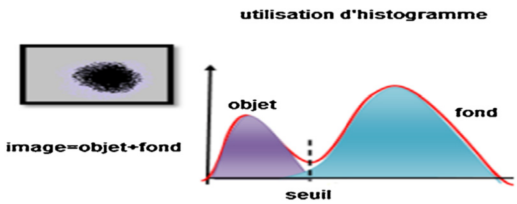

Fig. 6. Total Thresholding by use of histogram [36].

class "object" contains all the pixels of level of gray higher to S. In the mammography the classes c_2 (represents calcifications) and c_1 (represents high frequency elements caused by dense tissue) [20].

These two classes can be indicated according to the threshold S as follows:

$$c_1 = \{0, 1, \ldots, S\} \tag{7}$$

$$c_2 = \{S+1, \ldots, L-1\} \tag{8}$$

σ_w^2 is the variance of a class, σ_h^2 the variance between classes, and σ_T^2 is the total variance such as:

$$\sigma_B^2 = p_1 p_2 (u_2 - u_1)^2 \tag{9}$$

$$\sigma_T^2 = \sum_{i=1}^{L-1} p_i (i-u)^2 \tag{10}$$

$$\sigma_w^2(S) = \sum_{i=0}^{S} p_1 (i-u_1)^2 + \sum_{i=S+1}^{L-1} p_2 (i-u_2)^2 \tag{11}$$

with

$$\sigma_T^2 = \sigma_B^2 + \sigma_w^2 \tag{12}$$

u_1, u_2 and u indicate respectively the levels of average gray of classes c_1 and c_2, and the image such as:

$$u_1 = \sum_{i=1}^{S} i \cdot \frac{p_i}{p_1} \tag{13}$$

$$u_2 = \sum_{i=S+1}^{L-1} i \cdot \frac{p_i}{p_2} \tag{14}$$

$$u = \sum_{i=1}^{L-1} i \cdot p_i \tag{15}$$

p_1 and p_1 represent respectively the a prior probability of classes c_1 and c_2 such as:

$$p_1 = \sum_{i=1}^{S} p_i \tag{16}$$

$$p_2 = \sum_{i=S+1}^{L-1} p_i \tag{17}$$

$$p_1 + p_2 = 1 \tag{18}$$

The optimum threshold S^* can be given by maximizing one of the three following criteria:

$$\lambda = \frac{\sigma_B^2}{\sigma_w^2} \tag{19}$$

$$\eta = \frac{\sigma_B^2}{\sigma_T^2} \tag{20}$$

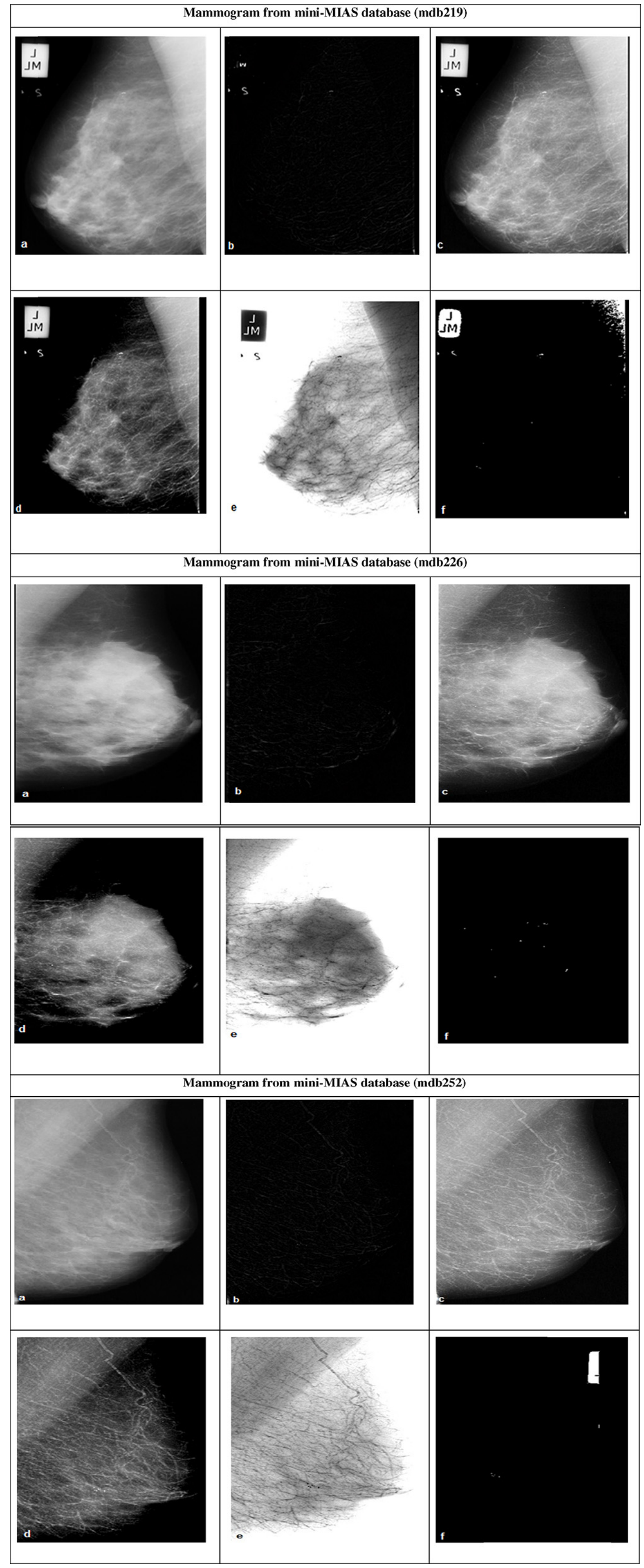

Fig. 7. Results relative to each stage of the proposed algorithm for the detection of benign calcifications: (a) mammography image with suppression of the noise by filter of Gaussian; (b) white Top-Hat transform; (c) raising of contrast (two white Top-Hat transform + image original); (d) complement of the enhanced image; (e) adjust the contrast of the enhanced image; (f) thresholding the algorithm of Otsu.

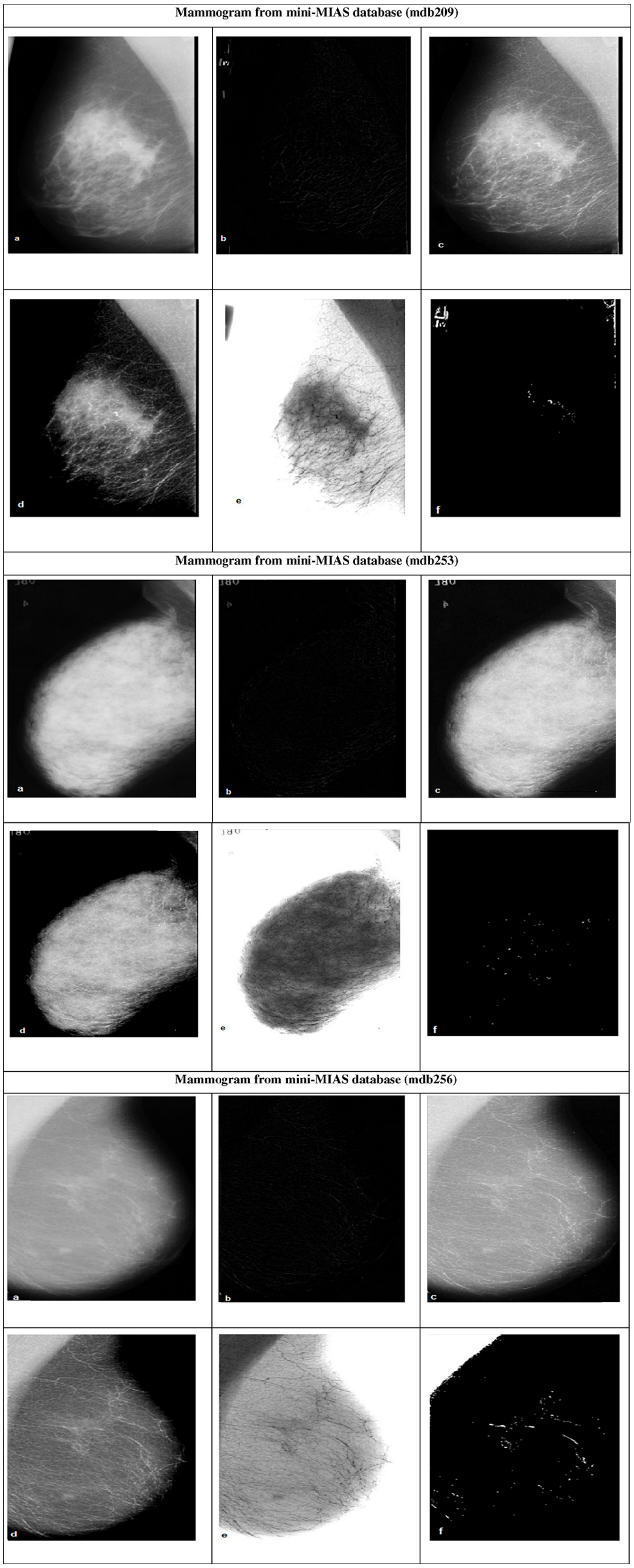

Fig. 8. Results relative to each stage of the proposed algorithm for the detection of malignant calcifications: (a) mammography image with suppression of the noise by filter of Gaussian; (b) white Top-Hat transform; (c) raising of contrast (two white Top-Hat transform + image original); (d) Complement of the enhanced image; (e) adjust the contrast of the enhanced image; (f) thresholding the algorithm of Otsu.

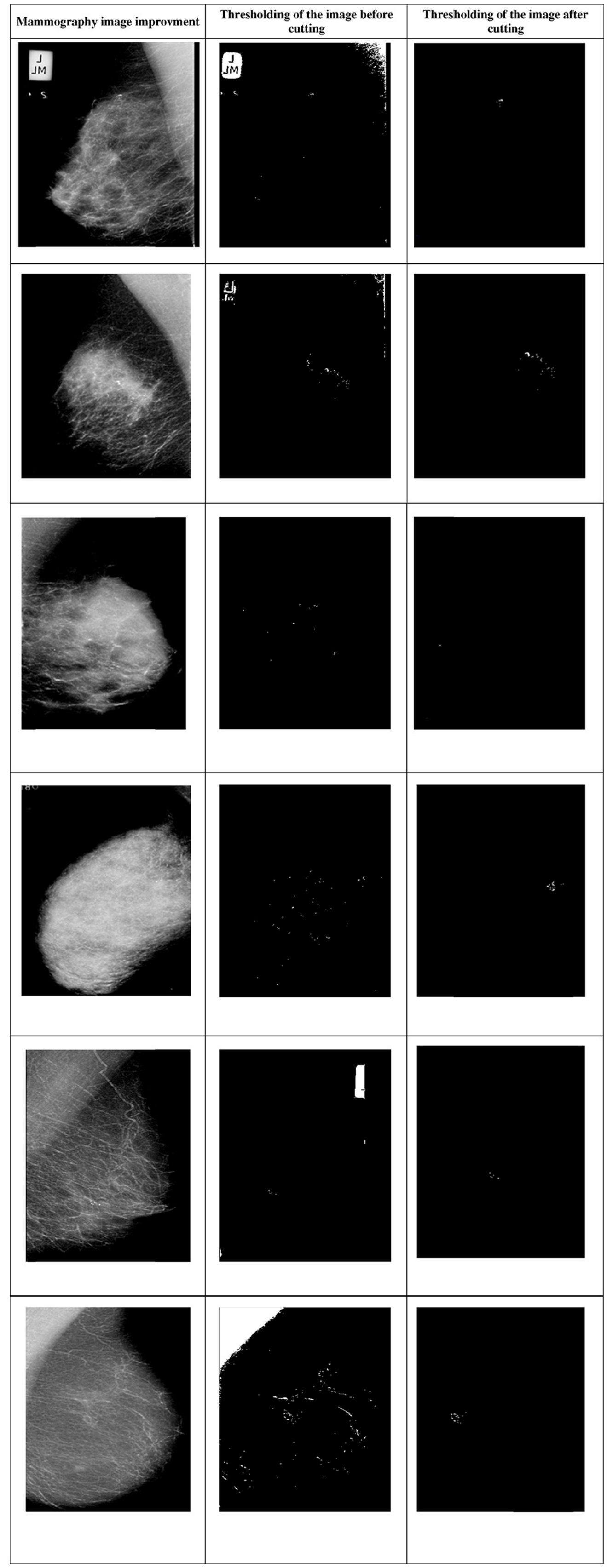

Fig. 9. Results of the proposed algorithm for the detection of calcifications before and after the redimensioning of the image by using the information annotated by the radiologist.

$$K = \frac{\sigma_T^2}{\sigma_W^2} \tag{21}$$

The three criteria are equivalent, but for reasons of simplicity, the variance between classes is used. The optimal threshold S^* is that which maximizes this variance:

$$\sigma_B^2(S^*) = \underset{0 \le s \le L-1}{\text{Arg max}} \sigma_B^2(S) \tag{22}$$

5. Experimental results

In this paper, we use the base of image MIAS (Mammography Image Analysis Society) [2]. These images of the type MLO (Mediolateral Oblique) are digitized with a resolution of 50 μm by pixel on 8 bits. The space resolution of each image is of 1024 × 1024 pixels. Various mammary pathologies resulting from the mini-MIAS database that are the object of our study, illustrate mainly benign and malignant calcifications. The mini-MIAS images used in the proposed CAD system are distributed as follows (see Table 1).

The detection of calcifications is very complex due, in one hand, to the diversity of their forms and, in the other hand, to the border badly definite between healthy tissue and the cancerous zone. For this reason, we propose an algorithm toward the improvement of the mammography image. To highlight calcifications; we selected several images of mini-MIAS database with dense fabric and the presence of calcification. The results are illustrated by Figs. 7 and 8.

Fig. 9 represents the thresholding of the image mammography before and after image division, by leaving only the area identified by the expert radiologists (see Table 2) [2].

6. Conclusion

An important challenge of research is to improve visual quality of the mammography by image processing in order to help the early detection of the breast cancer. It is well-known that mammography interpretation is a very difficult task, even with the availability of the experienced radiologists. However, the mammography of strong mammary density was not treated correctly. That is because of the lack of contrast between healthy tissue and the cancerous zones. Therefore, it appears to us that it is impossible to design an algorithm which gives good performances for all the images, which proves that the remained human interaction is necessary. Mathematical morphology proves to be a useful tool for the detection of calcifications in the digital mammography. In this work, we propose a new approach for the detection of calcifications on the mammography. We applied a technique of digital processing of the image, like an improvement of the image by using operations of mathematical morphology in order to improve contrast between calcifications and the background in the digital mammography. The extraction is done according calcifications white Top-Hat transform. The latter consist of a set of techniques based on a study of the objects according to their form, their size and their texture. The obtained results show that the methodology put in work was able to detect satisfactory calcifications.

References

[1] N. Otsu, A threshold selection method from grey-level histograms, IEEE Trans. Syst. Man Cybern. 9 (January (1)) (1979) 62–66.
[2] The mini-MIAS database of mammograms, 2014, available online at: http://peipa.essex.ac.uk/info/mias.htm.
[3] J.M. Mossi, A. Albiol, Improving detection of clustered microcalcifications using morphological connected operators, in: Proceedings of the IEEE International Conference on Image Processing and Its Application, vol. 2, 1999, pp. 498–501.
[4] Algerie360°, available online at: http://www.algerie360.com/femmes/femme-sante/cancer-du-sein-en-algerieplus-de-4500-deces-par-an/2012.
[5] H.C. Zuckerman, The role of mammography in the diagnosis of breast cancer, in: I.M. Ariel, J.B. Clearly (Eds.), Breast Cancer: Diagnosis and Treatment, McGraw-Hill, New York, 1987, pp. 152–172.
[6] H. Cheng, X. Shi, R. Min, L. Hu, X. Cai, H. Du, Approaches for automated detection and classification of masses in mammograms, Pattern Recognit. 39 (4) (2006) 646–668, Elsevier.
[7] L. Bocchi, G. Coppini, J. Nori, G. Valli, Detection of single and clustered microcalcifications in mammograms using fractals models and neural networks, Med. Eng. Phys. 26 (4) (2004) 303–312, Elsevier.
[8] C.C. Diaz-Huerta, E.M. Felipe-Riveron, L.M. Montaño-Zetina, Quantitative analysis of morphological techniques for automatic classification of micro-calcifications in digitized mammograms, Expert Syst. Appl. 41 (16) (2014) 7361–7369, Elsevier.
[9] C. Marrocco, M. Molinara, F. Tortorella, Detection of cluster of microcalcifications based on watershed segmentation algorithm, in: Computer-Based Medical Systems (CBMS), 25th International Symposium IEEE, Rome, 2012, pp. 1–5.
[10] H.D. Cheng, X. Cai, X. Chen, L. Hu, X. Lou, Computer-aided detection and classification of microcalcifications in mammograms: a survey, Pattern Recognit. 36 (12) (2003) 2967–2991, Elsevier.
[11] S. Halkiotis, T. Botsis, M. Rangoussi, Automatic detection of clustered microcalcifications in digital mammograms using mathematical morphology and neural networks, Signal Process 87 (7) (2007) 1559–1568, Elsevier.
[12] M. Rangaraj, Rangayyan, J. Fábio, J.E. Ayres, Leo Desautels, A review of computer-aided diagnosis of breast cancer: toward the detection of subtle signs, J. Frankl. Inst. 344 (3–4) (2007) 312–348, Elsevier.
[13] J. Quintanilla-Dominguez, B. Ojeda-Magaña, M.G. Cortina-Januchs, R. Ruelas, A. Vega-Corona, D. Andina, Image segmentation by fuzzy and possibilistic clustering algorithms for the identification of microcalcifications, Sci. Iran. 18 (3) (2011) 580–589, Elsevier.
[14] S. Anand, R. Aynesh Vijaya Rathna, Detection of architectural distortion in mammogram images using contourlet transform, in: International Conference on Emerging Trends in Computing, Communication and Nanotechnology (ICECCN) IEEE, 2013, pp. 177–180.
[15] X. Bai, F. Zhou, Infrared small target enhancement and detection based on modified Top-Hat transformations, Comput. Electric. Eng. 36 (6) (2010) 1193–1201, Elsevier.
[16] X. Bai, F. Zhou, B. Xue, Toggle and top-hat based morphological contrast operators, Comput. Electric. Eng. 38 (5) (2012) 1196–1204, Elsevier.
[17] A. Laine, S. Schuler, J. Fan, W. Huda, Mammographic feature enhancement by multiscale analysis, Med. Imaging 13 (4) (1994) 725–740, IEEE.
[18] W. Veldkamp, N. Karssemeije, Normalization of local contrast in mammograms, Med. Imaging 19 (7) (2000) 731–738, IEEE.
[19] K. Mcloughlin, P. Bones, N. Karssemeijer, Noise equalization for detection of microcalcification clusters in direct digital mammogram images, Med. Imaging 23 (3) (2004) 313–320, IEEE.
[20] J. Mohanalin, M. Beena mol, A new wavelet algorithm to enhance and detect microcalcifications, Signal Process. 105 (2014) 438–448, Elsevier.
[21] H. Yoshida, K. Doi, R.M. Nishikawa, M.L. Giger, Robert, An improved computer assisted diagnostic scheme using wavelet transform for detecting clustered microcalcifications in digital mammograms, Acad. Radiol. 3 (8) (1996) 621–627, Elsevier.
[22] N.-C. Tsai, H.-W. Chen, S.-L. Hsu, Computer-aided diagnosis for early-stage breast cancer by using wavelet transform, Comput. Med. Imaging Graph. 35 (1) (2011) 1–8, Elsevier.
[23] R. Mousa, Q. Munib, A. Moussa, Breast cancer diagnosis system based on wavelet analysis and fuzzy-neural, Expert Syst. Appl. 28 (4) (2005) 713–723, Elsevier.
[24] W. Zhang, H. Yoshida, R. Nishikawa, K. Doi, Optimally weighted wavelet transform based on supervised training for detection of microcalcifications in digital mammograms, Med. Eng. Phys. 25 (6) (1998) 949–956, Elsevier.
[25] A. Oliver, A. Torrent, X. Lladó, M. Tortajada, L. Tortajada, M. Sentís, J. Freixenet, R. Zwiggelaar, Automatic microcalcification and cluster detection for digital and digitised mammograms, Knowl.-Based Syst. 28 (2012) 68–75, Elsevier.
[26] B. Verma, P. McLeod, A. Klevansky, Classification of benign and malignant patterns in digital mammograms for the diagnosis of breast cancer, Expert Syst. Appl. 37 (4) (2010) 3344–3351, Elsevier.
[27] M. Farajzadeh, A. Mahmoodi, M.R. Arvan, Detection of small target based on morphological filters, in: Electrical Engineering (ICEE) 20th Iranian Conference IEEE, 2012, pp. 1097–1101.
[28] X. Bai, F. Zhou, Y. Xie, Ting Jin, Adaptive Morphological Method for Clutter Elimination to Enhance and Detect Infrared Small Target, in: Internet Computing in Science and Engineering (ICICSE), 08. International Conference, 2008, pp. 47–52.
[29] F.Y. Shih, V. Gaddipati, General sweep mathematical morphology, Pattern Recognit. 36 (7) (2003) 1489–1500, Elsevier.
[30] M. Zeng, J. Li, Z. Peng, The design of Top-Hat morphological filter and application to infrared target detection, Infrared Phys. Technol. 48 (1) (2006) 67–76, Elsevier.
[31] M. Mohamed Fathima, D. Manimegalai, Automatic Detection of Tumor Subtype in Mammograms Based On GLCM and DWT Features Using SVM, in: Information Communication and Embedded Systems (ICICES), International Conference IEEE, Chennai, 2013, pp. 809–813.
[32] X. Bai, F. Zhou, Analysis of new top-hat transformation and the application for infrared dim small target detection, Pattern Recognit. 43 (6) (2010) 2145–2156, Elsevier.

[33] M. Wirth, M. Fraschini, J. Lyon, Contrast enhancement of microcalcifications in mammograms using morphological enhancement and non-flat structuring elements, in: 17th IEEE Symposium on Computer-Based Medical Systems, 2004, pp. 134–139.
[34] S. Kumar, M. Pant, A.K. Ray, Differential Evolution Embedded Otsu's Method for Optimized Image Thresholding, in: Information and Communication Technologies (WICT), World Congress IEEE, Mumbai, 2011, pp. 325–329.
[35] J.Z. lui, N.Q. Li, the automatic thresholding of grey-level pictures via two-dimension Otsu method, acta automat, Sinica (in Chinese) 19 (1) (1993) 101–105.
[36] P.K. Saha, J.K. Udupa, Optimum threshold selection using class uncertainty and region homogeneity, Pattern Anal. Mach. Intell. 23 (7) (2001) 689–706, IEEE.