5th International Conference on Control Engineering&Information Technology (CEIT-2017)
Proceeding of Engineering and Technology –PET
Vol.34 pp.38-42

Automatic Semi Algorithmfor the Detectionof Micro calcificationsin the Mammogram

Mohamed Ali HAMDI

Institut National des Sciences Appliquées et de Technologie,
Laboratoire MMA
Carthage University
Centre Urbain Nord BP 676-1080 Tunis, Tunisia

Abstract— **In the setting of the automatic analysis of the mammograms, the detection of opacities of the breast is a multifaceted well-known difficulty whose viability remnants to be established again. We present in this work a method of filtering in order to detect the micro calcifications in mammography's images even as achieving a more effective algorithm.**

***Keywords*— Mammogram; micro calcifications, Sequential Alternate filtering; Morphological opening and closing**

I. Introduction

The objective of mammography examination is the re-search of probable supposed radiological signs that is translating lesions of the mammary gland. in the middle of them, opacities communicate to the anomalies on-density beaches. Opacities differentiate themselves from the normal structures of the mammary gland by a certain number of more or less variable features according to the topic and the nature of the opacity: the shape, the contrast, the contour, the texture...[1]. In this context, the problem of the implementation of an artificial vision system resides globally in the difficulty to create a model of the problem and to automate a complex analysis based on experience. The aim of this work is the elimination of the impulsive noise resulting of the image segmentation of mammogram. With the purpose of comparison we carried out some experiments with different morphological operators, arriving to the final conclusion that the best results are obtained with generalized morphological operators. Digital images enhancement, specifically noise re-duction and smoothing, have been an important topic of researching in digital image processing (DIP). Many applications associated with this thematic have acquired great importance in different fields of DIP, among others, in digital image restoration, image reconstruction and segmentation and transmission of images [2],[3],[4].In many image processing tasks, segmentation is an important step toward image analysis. It allows quantification and visualization of the objects of interest. Recently, image segmentation methods were extensively reviewed by Sijbers et al [5]. They concluded that segmentation of medical images is so far a difficult task and fully automatic segmentation procedures are far from satisfying to specialists in many realistic situations. Nevertheless, efforts towards the solution of the segmentation problem are motivated by the variety of applications wherein segmentation plays a crucial role [6].

II. Description of our METHOD

The difficulty of our problem resides, to a large extent, in the complexity and the diversity of the images and the objects (opacities) to study. The various perceptible components of the centre on the stereotypes mammographic (grease, fibres conjunctive and possibly lesions) make particularly the images complex; moreover the characteristics of these elements (size, intensity, contrast, forms…) can vary in a radical way from one image to another.

The numerical mammograms on which we worked were provided by the base of data MIAS (Mammography Image Analysis Society

.

A. Sequential Alternate filtering

One carried out a sequential alternate filter in our algorithm to avoid them over-segmentations due to the radiographic noise ("mottle") in the system film-screen which is defined like the random fluctuations of the optical density on a uniform image. The principal sources of radiographic noise are: the quantic background noise, the grain of the screen, the grain of film, the artefacts of development, conversion X-ray-light and In the numerical systems, are added the electronic noise of the detectors and the monitors of visualization.

One points out q' a morphological filter is an operator who must checks the growth and the idempotence, one uses for that a succession of openings and closings. In a family rises from filters called alternate filters.

A sequential alternate filter (SAF) of size B noted is obtained by iteration of openings and of the same closings cuts: $\gamma_B \circ \phi_B$ or $\phi_B \circ \gamma_B$ or $\gamma_B \circ \phi_B \circ \gamma_B$

In filtering of images, it is often necessary to eliminate from the noise represented by small dark or clear spots. Erosion will eliminate the clear spots and dilation the dark spots. These operators however will also modify the objects thus to be studied one obliged to use closing and the opening.

- The opening of X by B:

ISSN 2356-5608

$$\gamma_B(X) = (X \Theta B) \oplus B \quad (1)$$

- The closing of X by B:

$$\phi_B = (X \oplus B) \Theta B \qquad (2)$$

Thus the opening and closing are two operators dual:

$$\gamma_B(X) = [\phi_B(X^C)]^C \quad (3)$$

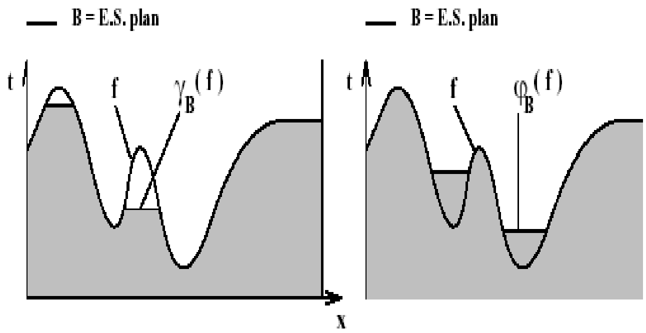


Fig.1Morphological opening and closing

The application of a sequential alternate filter on numerical mammograms of size 1024x1024 gives:

Fig. 2 Morphological filtering by a SAF

B. *Extraction of the extrema and marking*

The concepts of regional maximum and minimum are not local: in the general case, one cannot decide if a pixel p belongs to an extrema simply in examining the pixels close to p. It is necessary to traverse the whole of the plate containing p. [8]

This is why one generally speaks about regional maximum and regional minimum. If the thresholds of F are considered, a maximum of altitude H of this function will be a related component of the threshold $X_h^+(f) = \{x \in Z^2, f(x) \geq h\}$ not containing any related component of any threshold $X_s^+(f)$ where*s*>*h*. Lastly, a regional M of F of altitudeH, satisfied maximum $\forall h' > h, X_{h'}^+(f) \cap M = \varnothing$ [7]

The maximum ones of altitude H of F are thus the components of $X_h^+(f)$ not rebuilt by $X_{h+1}^+(f)$, that is to say still the components of $X_h^+(f)$ not rebuilt by $X_h^+(f-1)$.

The second difficulty is of order practical: the concept of extrema is very sensitive to the noise. A structure marked by only one regional maximum will be marked by several extrema, a solution with this problem consists in filtering the image of kind to eliminate the structures (and the corresponding extrema) non significant: the compositions of openings and closings for example make it possible to filter the structures of small size while preserving those of more significant size. This point is carried out in the stage of filtering SAF. [9]

Since the art of the segmentation by LPE lies in the development of the image of the markers. The techniques employed go from manual marking to employs sophisticated automatic methods. The numerical rebuilding, there still, will be largely made profitable.

C. Selection of markers according to a criterion of size or form

When the signal report/ratio with noise is extremely weak, the space coherence of the points, which is morphological character, allows us, by looking at the image, to identify the objects present. It is here the capacity of space integration of our perception which helps us to extract an object from this scene. For proof, an enlarging or a profile of the zone where we see a transition object-bottom reveals that no local information would authorize to detect this transition. This type of image is characteristic of the cases where discrimination by contrast fails whereas the criteria of size or form give good results.

The top hat HdF is very useful to extract from the clear or dark objects according to criteria's of size or form. It can prove that one has such information on the objects having to be used as marker. We will use HdF to create an image of markers. One can, makes some separately define the markers of the bottom and those of the object by calculating HdF and HdF *. [10]

Thus the top hat is formed by the residues of the opening, i.e. the clear and narrow zones which are eliminated at the time of the opening:

$$HdF(f) = f - \gamma_B(f) \quad (4)$$

In the same way, to reveal the dark and narrow zones, one will be interested in the top hat combined made up of the residues of closing:

$$HdF^*(f) = \phi_B(f) - f \quad (5)$$

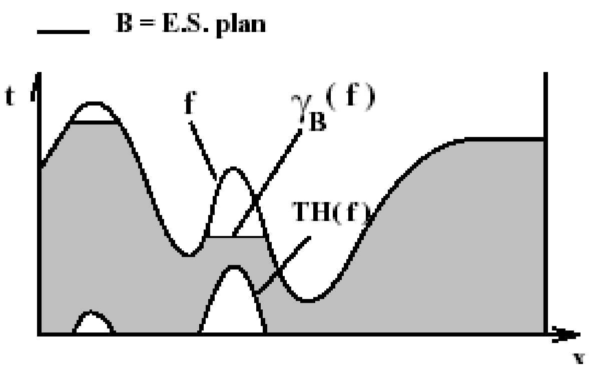


Fig. 3 Top HAT

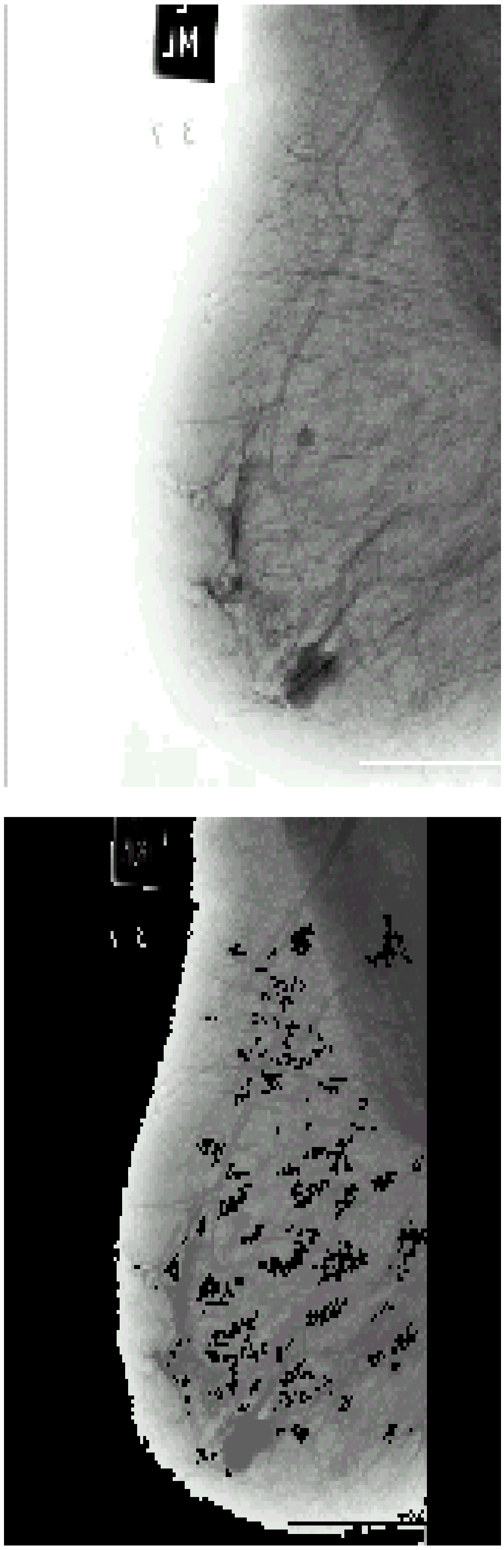


Fig. 4 Marking by top hat of the mammography

III. SEGMENTATION OF THE MICROCALCIFICATIONS

The following stage consists in extracting the areas from interest in breast: over-densities. We do not speak yet about abnormal over-density because this distinction will be carried out only in one following stage. Here, our goal is to correctly segment all the over-densities present in the breast, which are pathological or not, and this some is their size or their form…

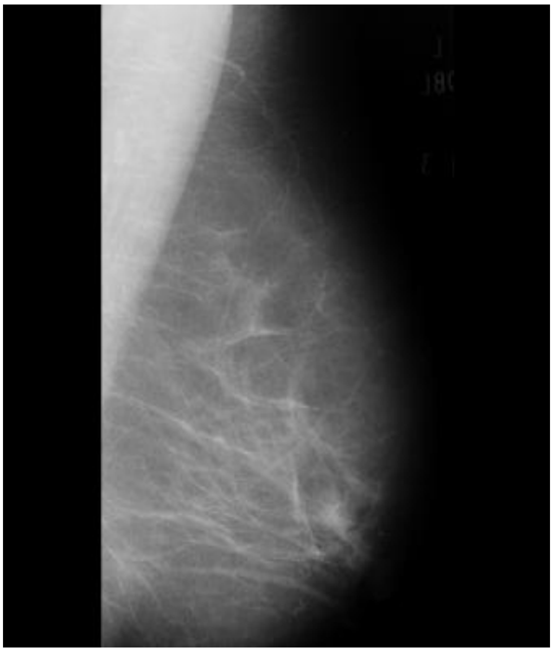
On the digitized mammograms, an over-density corresponds to an area with strong Contrast. This term is rather not very precise but completely characteristic of reality. Indeed, the over-densities of interest can have on the stereotype a contrast of a very low or very large value according to their nature, the nature of the centre (dense or clear), their position in space… In spite of that, contrast (i.e. dynamics) remain the most relevant characteristic to extract these over-densit' are. We thus use an algorithm of segmentation based on the LPE; the markers of the over-densities are obtained by considering the maximum ones of stronger dynamics (dynamic calculated on the original image).

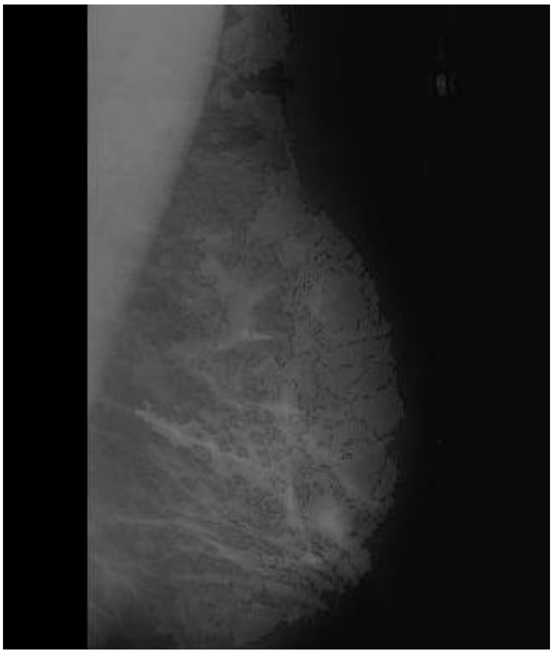
This algorithm is thus far from parametric: only one threshold in contrast is necessary. This threshold is fixed by the minimal contrast of the over-densities which the system must detect. One of the large assets of this algorithm is to give a correct segmentation for all required areas of the image: whether they are of small or big size, of form round (like certain opacities) or lengthened (like the fibrous structures), of weak or strong contrast, homogeneous or not, with well defined or dubious contours (even if the result remains approximate when part of information relating to contour misses). The good quality of the segmentation obtained can only facilitate the following stage of our algorithm: selection among the segmented candidates of the abnormal over-densities (or all at least suspect).

The following examples illustrate the behaviour of the algorithm of segmentation in particularly difficult cases: opacities are hidden in the mass fibrous surrounding; a portion of their contour misses. The inaccuracy on contours which one extracts is with the measurement of the visual inaccuracy on contours of these opacities.

One sees it on these examples, one in particular segments a great number of non pathological structures (of the fibrous structures) and this number is all the more significant as the centre is dense. The information of contrast to select the areas having to be segmented. Another solution could have consisted in more severely selecting these areas by introducing additional knowledge (to take into account the form of the areas, for example, can make it possible to eliminate the markers from the fibrous structures). We preferred to carry out this sorting in a following stage, so as to very clearly separate the stages from segmentation and selection.

We tested this algorithm on a basis of 24 images. In all the cases, them suspect over-densities are extracted and correctly segmented (contours are poor only in particularly difficult cases). Lastly, the number of extracted non suspect over-densities is a function of the texture of the centre (this number can be very significant for the dense centres and is most of the time very weak for the clear centres).





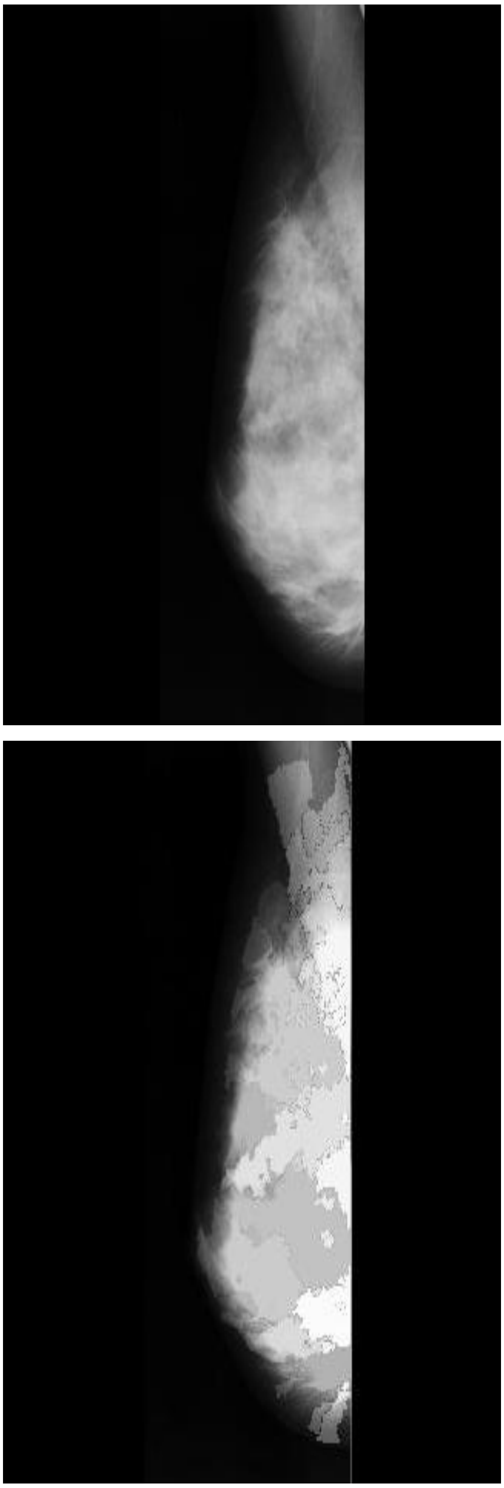


Fig. 5 segmentation of the mammograms by using the semi-automatic algorithm

IV. CONCLUSION

The study undertaken for the automatic control of opacities did not reach its final point yet.

However, of the significant stages were crossed in this field up to now unexplored. First of all, this study made it possible to however show the feasibility of the application the manual spot the always present (correction by closing, addition, dilation and the iteration) thus analysis visual remainder always the reference mark to pass from one stage to the other. Then, the results obtained for the segmentation part, which is more specifically of the field of the analysis of image, are very encouraging even if if certain improvements must still be produced, in particular to improve the sensitivity of the algorithm with respect to the conditions of radiography and digitalization

.

REFERENCES

[1] S. Aramvith; H. Kortrakulkij; D. Tancharoen; S. Jitapankulsource-channel coding using simplified block-based segmentation and content-based rate-control for wireless video transport, Ph.D Thesis, America 2015.

[2] M., Roberto ,Rodríguez: "La interaction el concilient heuristique en la restauration y el majoraient digital de imagines. Un system intelligent (SIPDI)", PhD Thesis, ISPJAE, Habana, 1995. 1995.

[3] Kak, A , Rosenfeld, A. "Digital Picture Processing", Academic Press, Inc., New York, 1976.

[4] Woods, R. E.; González, R.; Rodríguez, D..; Ruíz, S. Y; Joyanes, A. L.: "Raiment digital de imagines", Addison-Wesley IberiaAmericana S.A, Limington, Delaware, EUA, 1996.

[5] Scheunders,Sijbers, J, P.; Verhoye, M.;et al.: "Watershed-segmentation of MR for Quantization", Vol. 14, No17, 2008.

[6] Pratikakis, I.: "Watershed-driven image segmentation", PhD thesis, Vie Universities Brussels, 2004.

[7] F. Meyer and S. Beucher. Morphological segmentation. Journal of Visual Communication and Image Representation, 11, No 1:21-46, 1990.

[8] F. Meyer, A. Oliveras, P. Salembier, and C. Vachier. Morphological tools for segmentations: connected filters and watershed. Annals of telecommunications, 1997.

[9] P. Salembier. Morphological multiscale segmentation for image coding. SIgnal Processing, 38(3):359-386, 1994.

[10] L. Vincent and P. Soille. Watersheds in digital space and e±cient algorithm based on immersion simulations. IEEE Transactions on PAMI, 13(No. 6):583-598, 1991.