# Segmentation of the Breast Masses in Mammograms Using Active Contour for Medical Practice: AR based surgery

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**Abstract.** Images have been one of the most important ways humans have used to communicate and impart knowledge and information since the dawn of mankind, as an image can encompass a large amount of information concerning the quality of life linked to health and particularly in oncology precisely the breast cancer. New technologies such as Augmented Reality (AR) guidance allows a surgeon to see sub-surface structures, by overlaying pre-operative imaging data on a live laparoscopic video. The presence of masses in mammography is particularly interesting for the early detection of the breast cancer. In this article, we propose to use a mass detection system, based on two main axes: segmentation and pretreatment. The latter is based on the suppression of the noise by a Gaussian filter and mathematical morphology (white Top-Hat transform) in order to bring out all the spots (Clear Spots) possible to be pathologies. In the second axis, we are interested in the segmentation of pathologies in mammography images. This consists of segmenting the object of interest by active contour models (Chunming Li). 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 masses starting from the mammography referents from the database Mini MIAS. The proposed breasts masses detection can, thus, provide an acceptable accuracy for an AR-based surgery or medicine courses with scene augmentation of videos, which provides a seamless use of augmented-reality for surgeons in visualizing cancer tumors.

**Keywords:** Augmented Reality; Mammography; Masses; Mathematical Morphology; Transformation Top-Hat; Chunming Li; Active Contour; Gaussian Filter; medical practice; scene augmentation.

## 1 Introduction

Recently, medical imaging (MI) is an extraordinaire Tool for clinical Diagnosis. It could be the best way to quick detect and localise complex human disease such as breast cancer. In fact, breast cancer is the first cause of death in women [1]. In Algeria, breast cancer registered 11,000 new cases per year, in the advanced stage of pathology [2]. Efficient diagnostic is an important key to prevent breast cancer and the treatment could be more useful. One of the most important research in this area is about the detection and analysis of cancer. In this case, mammography remains an essential reference technique for breast exploration, the most effective in the field of surveillance and early detection of breast cancer [3], [4], [5], according to radiologist, mass and calcification are parts of quiet calcium, and there are also the celles is usuelle non-cancers but is an important indicator of breast cancer. If 80% of them are benign tumors, only 15% of breast tumors are malign, where the diagnostic was being by mammography [6]. In order to reduce the workload of radiologists, the design of a computer-assisted detection system (CAD) based on medical images processing algorithms is requested. It is based on a three-step workflow: detection, analysis and classification. Automated detection of breast diseases is always difficult, even for experienced radiologists. To date, some algorithms described in the literature have been applied to detect masses in the mammogram, whether benign or malign. Among the proposed methods, those that use the representation of mammography based on improved contrast by white Top-Hat transform of mathematical formation [7] and [8]-[14]. This paper attempts to introduce improvements based on the pathway and mathematical morphological factors applied to different gray levels images [6]. The latter provides time to extract the desired masses. In the second phase, we use a segmentation of the area of interest for the identification of masses, based on the active contour models (Chunming Li) [15]. The method suggested has been tested on several images from the Mini MIAS database of mammogram [16], the obtained results allowed higher and accurate segmentation rates. Fortunately, Augmented Reality (AR; i.e., synthetic vision) has been successfully implemented in some areas of surgery [17], [18], [19]. Augmented and Virtual Realities have invaded several Healthcare domains: Rehabilitation [20], emotion recognition [21], [22] and [23], educational technology by AR, for facilitating to explain complex medical situations for medical students [24], AR is an enhanced reality generated by a computer that is superimposed on a real-world environment. The purpose of AR in surgery is to combine preoperative data, such as MRI volumes, and fuse the data onto the intraoperative real-time environment [17]. For instance, in breast cancer surgery, AR can be used to generate a virtual scene that contains augmented videos of the patient’s anatomy. These videos can act as a visual guide for surgeons in determining the tumor and lymph node location, which, in turn (Fig. 1), should improve the overall efficiency and safety of the procedure. Displaying AR content can be done in several ways, such as video-based, see-through based, or projection based.

**Fig. 1.** Medical practice: AR-based surgery.

The following of the paper is organized as follows: after giving a short review in breast pathology diagnostic in Section 1, we provide the proposed detection method. Tests and experiments of our approach is given in Section 3. Discussion and future work are presented in Section 4.

## 2 Proposed System

Figure 2 presents the proposed method for the detection of breast disease that helps improve and exposure masses in digital mammography. Here are the main steps conducted to achieve the proposed method. (1) Noise reduction by suppression of the noise by the Gaussian filter and the improvement of contrast between masses and the background-digitized mammography. (2) We will make an effort in the improvement of contrast by the operations of the mathematical morphology (by using a morphological transformation Top-Hat). In the third phase, the using a segmentation of the area of interest for the identification of mass. It exploits the result of description (which itself exploits the result of segmentation) to be able to decide the pathological nature of the mass, based on deformable models (active contour).

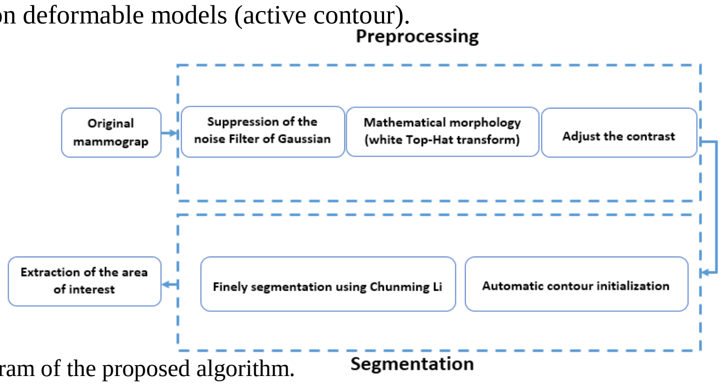


**Fig. 2.** Block diagram of the proposed algorithm.

### 2.1 Pretreatments stage

Despite the efforts of the related work, the detection of mammary pathologies remains difficult. Thus, an additional research effort based on two main steps is examined to achieve the objective of the proposed method, as follows.

**Step (1).** Due to the small size and low intensity of the mass, designing a filter is a very difficult task, has been applied to filter the noisy images and preserving the details and contours while filtering the homogeneous areas. The main objective pursued by the Gaussian filter is to filter the image by the reduction of the noise in the presented areas while avoiding the smoothing of the contours. 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: μ: Average ; and σ: Standard deviation.

It is clear that the Gaussian filter enhances the contrast of the contours with region smoothing and a partial reduction of the volume effect. Figure 3 shows of the typical histogram of a mammogram. Clearly, we distinguish three different classes of the pixels [23] and [25]:

- Class 1: the pixels of low of intensities.
- Class 2: the pixels having corresponding gray values within itself.
- Class 3: the pixels of high intensity, the large peak corresponding to the pectoral muscle, annotations and may be to breast lesions.

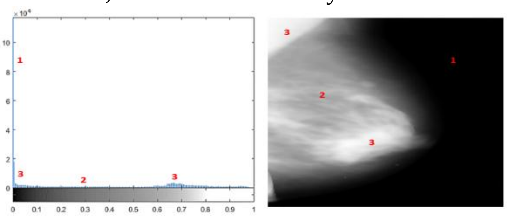

**Fig. 3.** The typical histogram of a mammogram.

Fig. 4 shows the visual results when comparing the original mammography image before and after applying the Gaussian filter. It is clear, can easily be interpreted that the Gaussian filter accentuates the sharpness of the edges, the smooth areas, and even decreases the effect of partial volume.

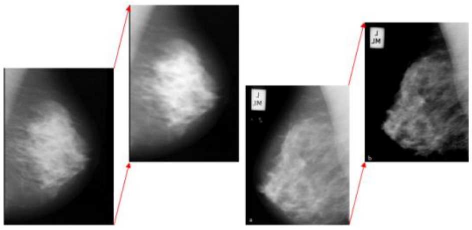

**Fig. 4.** Visual results comparison of the: a) Original mammography image; b) before and (c) after filtering.

*Step (2).* Mathematical morphology is a science of the form and structure. The basic principle of mathematical morphology is to compare the objects, which one wants to analyze with another object of reference, with size and form known, 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 [8] and [25]. F is an image in levels of gray and E is a structuring element. Dilation and erosion of F(x) from y(x), noted $F \oplus E$ and $F \ominus E$, are defined respectively as follows:

$$\mathrm{F} \oplus \mathrm{E} = \max_{\mathrm{u,v}}\big(\mathrm{F}(\mathrm{i}-\mathrm{u}, \mathrm{j}-\mathrm{v}) + \mathrm{E}(\mathrm{u,v})\big) \quad (2)$$

$$F \ominus E = min_{u,v}(F(i+u, j+v) - E(u,v)) \quad (3)$$

With: F(x): Corresponding to the small clear zones of the image. x: x(i, j): Is a point of an image, and y: y(u, v): are the sizes of the structuring element E.
E(y): Structuring element.

### 2.2 Segmentation method

In our work, we used the segmentation method based on the geometric deformable model (Chunming Li) [15] for the extraction of regions of interest. In order to eliminate non-suspect regions and for greater precision, the segmented image is presented to the expert in order to allow him to select from among the segmented regions, that which will be called the region of interest [15] and [26]. After selection of the region of interest by the expert, comes the role of the active contour detector. We used this algorithm in order to extract only the region of interest apart.

**Chunming Li model algorithm.** Below we present the most important equation used in this algorithm.

- Initialization : using the following equation

$$\text{if } \phi_0(x, y) = -\rho \qquad (x, y) \in \Omega_0 \tag{5}$$

$$\text{if } \phi_0(x, y) = 0 \qquad (x, y) \in \partial\Omega_0 \tag{6}$$

$$\text{if } \phi_0(x, y) = \rho \qquad \Omega - \Omega_0 \tag{7}$$

- Loop: for n = 1: Niter

Calculation of evolution function:

$$\frac{\partial\phi}{\partial t} = \mu\left[\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] + \lambda\delta(\phi)\mathrm{div}\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + vg\delta(\phi) \tag{8}$$

Evolve the model using the evolution equation:

$$\phi_{i;j}^{k+1} = \phi_{i;j}^{k} + \tau L\left(\phi_{i;j}^{k}\right) \tag{9}$$

Until convergence or until n = Niter.

- End of loop

*Implementation details of algorithm.* In this part, the proposed segmentation method has been applied to the mammographic images for the extraction of the area of interest. We first present the results obtained after the preprocessing and initialization of the contour towards the boundaries of the area of interest. Then we present the results obtained from the segmentation by the active contour approach (Chunming Li model). The contour is chosen automatically. The number of iterations for the detection of the active contour increases with the size of the area of interest [15]. This work was carried out within the IRVA team of the CDTA in Algiers, with a computer equipped with the Intel i3 processor (3.20 GHz) and 6 GB of RAM. And for programming, our application was coded by the Matlab programming language (R2020b). The diagram presented in Fig. 4 summarizes the several stages which we have proposed in an algorithm using Matlab functions for segmentation the masses is considered one of the most powerful programming languages in the medical field.

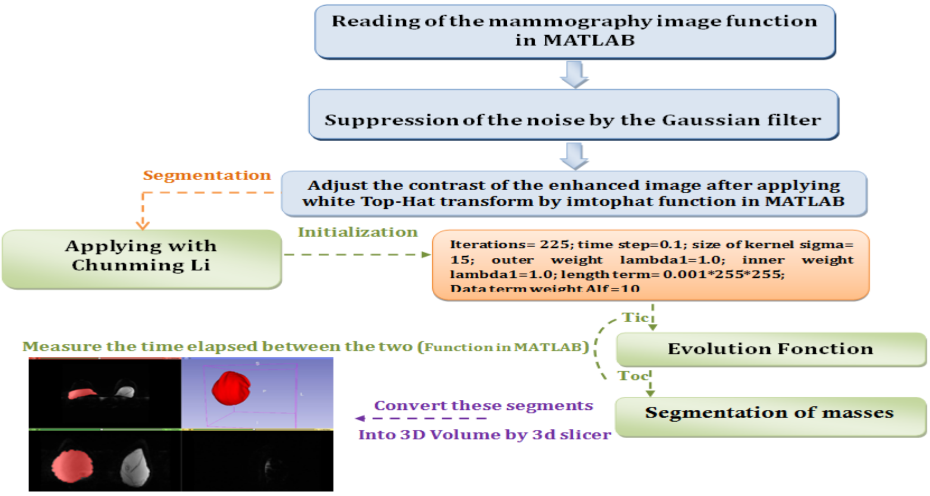


**Fig. 4.** Diagram of the proposed algorithme for the segmentation of masses.

## 3 Experimental results and discussion

In this work, the proposed method was tested using the mini-MIAS dataset from Mammography Image Analysis Society [16] to segment and illustrate primarily benign and malignant masses. A total of 66 images are examined with different mammary pathologies of the database mainly illustrate 34 benign masses and 32 malignant masses. The detection of masses is very complex due, on the one hand, of the diversity of their forms and, on the other hand, of the border badly definite between healthy tissue and the cancerous zone. For this reason, we propose an algorithm towards the improvement of the image mammography. To highlight masses; we selected several images of Mini MIAS database with dense fabric and the presence of masses. The results are illustrated by the figures below (see Fig. 5).

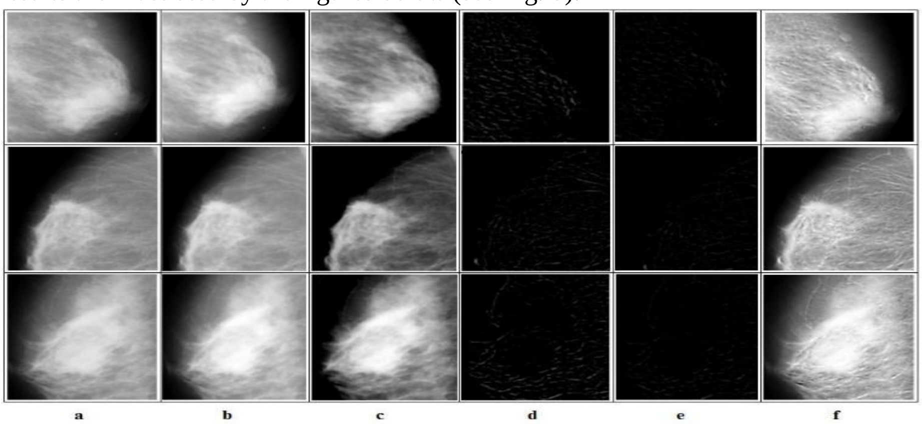


**Fig. 5.** Illustrate the visualization results of the pre process stage with: a) Original image; b) white Top-Hat transform; c) Raising of contrast (two white Top-Hat transform + image original); d) Complement of the raised image; E) improvement of the intensity of the image; f) Overlay of the previous process result with original image.

Noting that, this study confirms the performance of the image mammography improvement by the white Top-Hat transform for the detection of masses. In the second part of experimental results, the proposed segmentation method has been implemented in the context of identifying the main mammography tissues and extracting the mass area (see Fig. 6). This will subsequently allow the calculation the mass characteristics in order to classification that will be registered in the database.

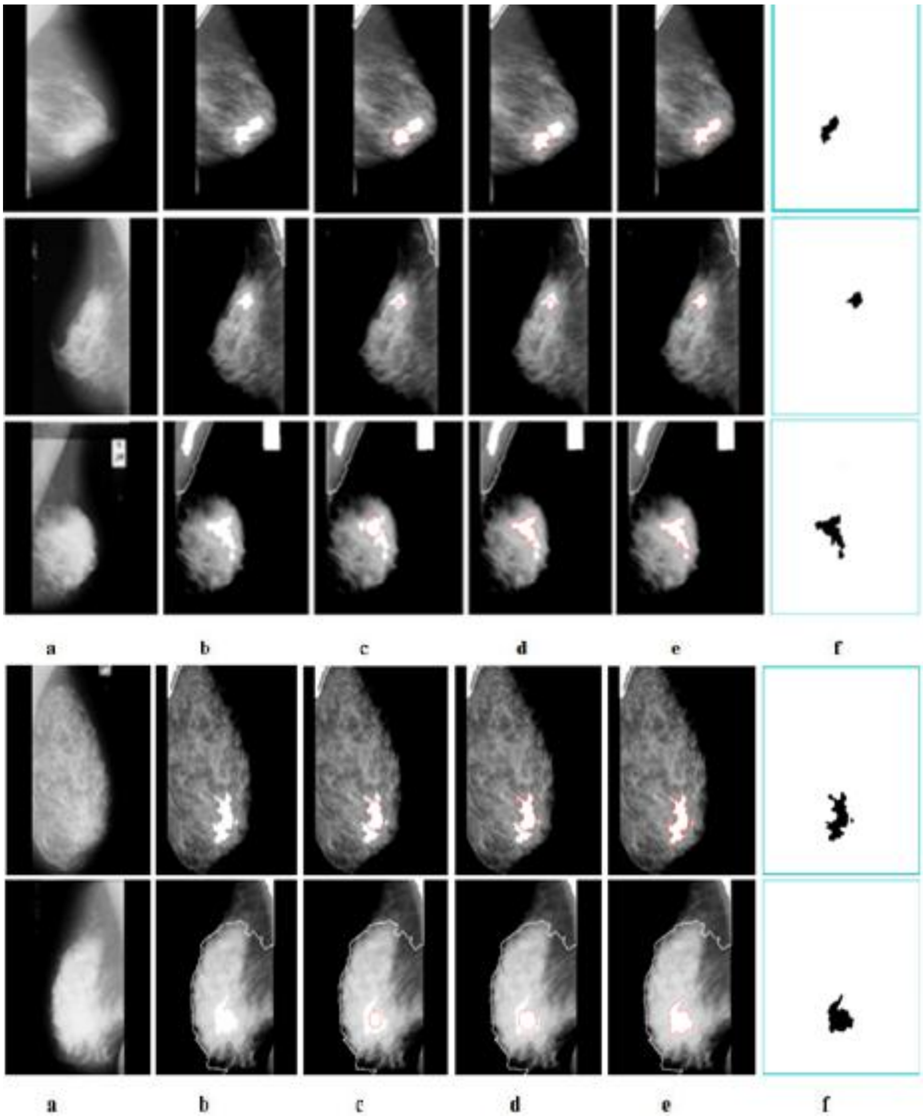


**Fig. 6.** The results of the Chunming Li model segmentation algorithm of the image. a) Initial image b) Mammography image after preprocessing; c) Automatic contour initialization; d) The evolution of the contour; e) The final image with the Chunming Li model; f) extraction of the separate area of interest.

For performance, comparison purposes our performance results with the performance results of mass detection studies in the literature Through Receiver operating characteristic (ROC), where availability analysis and graphs are commonly used in medical decision-making. The segmentation performance can be estimated by describing random errors (True positive; True negative; False positive; False negative), a measure of statistical changes (eq.10).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{10}$$

In addition, the obtained results show that by applying the proposed enhancement and segmentation the contour of mass, with compared other algorithms results cited in the literature Table 1. The table summarizes the results of this work in terms of precision and shows the great performance of our approach.

**Table 1.** Comparison of results obtained through our approach with other ones in the literature.

| Author | Segmentation method | Database | Accuracy |
|---|---|---|---|
| Rahimeh and al [27] | **Region growing algorithm** | MIAS and DDSM | 96.4% |
| Burcin and al [28] | **Otsu algorithm** | MIAS | 93.2% |
| Guerroudji and al | **active contours** | MIAS | 97.09% |

## 4 Conclusion

In computer vision, this vast field of research at the crossroads between mathematics, signal processing and artificial intelligence, the segmentation of images is a very delicate and by no means easy task. It requires precise knowledge of the images, their nature and the field of application. In this paper, we have developed a very efficient segmentation algorithm: Chunming Li, for the detection of breast pathologies. First, we applied a digital image processing technique in order to improve these images using mathematical morphology operations to improve contrast and background in the digital mammography image shot. Subsequently, we implemented a segmentation technique based on the active contours Chunming Li model for the detection of pathologies. The Chunming Li contour segmentation approach shows good results in locating the contours of the regions of interest if the initialization of these contours is not too far from the final contours. In future, in order to improve the accuracy as well as diagnostic. We will suggest an AR 3D visualization system and manipulation for Breast masses segmentation, which remains a very broad field of research.

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