

PAPER • OPEN ACCESS

Space-occupying lesions identification in mammary glands using a mixed computational strategy

To cite this article: S Vargas *et al* 2019 *J. Phys.: Conf. Ser.* **1414** 012016

View the [article online](#) for updates and enhancements.



IOP | ebooks™

Bringing you innovative digital publishing with leading voices to create your essential collection of books in STEM research.

Start exploring the [collection](#) - download the first chapter of every title for free.

Space-occupying lesions identification in mammary glands using a mixed computational strategy

S Vargas¹, M I Vera², M Vera³, J Salazar-Torres³, Y Huérfino², O Valbuena³, and E Gelvez-Almeida³

¹ Facultad de Ingeniería, Universidad Simón Bolívar, San José de Cúcuta, Colombia

² Facultad de Ciencias, Universidad de Los Andes, San Cristobal, Venezuela

³ Facultad de Ciencias Básicas y Biomédicas, Universidad Simón Bolívar, San José de Cúcuta, Colombia

E-mail: m.avera@unisimonbolivar.edu.co

Abstract. The mammary pathology can manifest itself in multiple ways and originates space-occupying lesions. The breast cancer is a space-occupying lesion, which is highly prevalent, especially in women, and worldwide it is one of the leading causes of morbidity and mortality in this population. The main image modality for breast cancer detection is the magnetic resonance but this kind of image modality introduces several imperfections that affect the image quality. Some of these imperfections or problems are: inhomogeneity in the anatomical structures, rician noise and artifacts. These problems make the analysis of the image information a real challenge. To address these problems, in this paper, we propose a computational technique able to extract a space-occupying lesion linked to breast cancer, present in magnetic resonance images. For this, the original image is processed with statistical-arithmetic filters and segmentation algorithms based on thresholding and multi-seed region growing techniques. The results, based on Dice score, show that the proposed technique is suitable for segmenting the breast cancer due high correlation between semi-automatic and manual segmentations. This technique can be useful in the detection, characterization and monitoring of this type of cancer and it can let to medical doctors to realize their work more efficiently.

1. Introduction

In the human beings, the mammary glands are two anatomical structures localized on anterior and superior thorax's face [1]. The benign pathologies in this kind of glands deepen of the patient symptoms such as tumor, secretion, pain or shape mamma alterations [2].

On the other hand, the breast cancer is the accelerated and uncontrolled growing of cells in the glandular epithelium, which link it with the normal lobules and shot lobules [2]. The statistics about breast cancer are alarming. This type of cancer is the most common diagnosed cause of death from cancer in women in the world [3]. Additionally, the modalities of medical imaging play a crucial role in the diagnosis of focal mammary lesions. Magnetic resonance imaging (MRI) is the primary diagnostic method for mammary lesions tumors. Using the magnetic resonance, we can visualize, in a very precise way, the vascular neoplastic infiltration, which greatly facilitates the planning of an additional treatment [4].



During acquisition image process the MRI several physics phenomes can introduces undesirable effects such as inhomogeneity, noise and artifacts affecting the information presents in the breast medical images. These problems make the analysis of this information a real challenge.

The segmentation of space-occupying lesions (SOL) is a problem of great interest because the three-dimensional (3D) segmentation of SOL from MRI images is a prerequisite for computer-assisted diagnosis, treatment planning and breast cancer control [5].

Several works related to the segmentation of breast cancer segmentation, which are presented at next. In this sense, Singh, *et. al.* considering x-ray images and they develop an automated system to detect tumors in the breast and shape classification using conditional generative adversarial network and convolutional neural network (CNN) techniques [6]. They report a Dice score (Ds) of 0.94 when comparing the manual and automatic segmentation. Dhungel, *et. al.* proposes an automatic technique based on belief networks for breast cancer detection and segmentation lesion [7]. The Ds obtained, in this research, was 0.89 considering 274 breast images. Additionally, Zhu, *et. al.* proposes a technique to detect mammary tumors, present in 158 mammographic images, using fully convolutional network. They report a Dice score of 0.97 [8]. Finally, Su, *et. al.* presents a strategy based on fast scanning CNN (fCNN) method for reducing the information loss and for global features extraction in order to segment breast cancer in digital mammography images. A value of 0.85 is obtained for these researchers for the Ds [9].

In this paper, the main purpose is to generate a semi-automatic non-lineal computational technique (NLCT) for the segmentation of the mammary tumor in magnetic resonance images. This technique is based on the application of a filter bank (median, saturation and enhancement filters) and region growing technique in order to generate the 3D mammary tumor morphology. This technique can be useful in the detection and monitoring of breast cancer with the objective of establishes the clinic or surgical actions oriented to address this type of pathology.

2. Materials and methodology

2.1. Dataset

A three-dimensional MRI database was used, which has a voxel number of 512 x 512 x 31. Manual segmentation of the mammary tumor by a mastologist is also available.

2.2. Computational strategy proposed

In Figure 1, a schematic diagram is presented. It synthesizes the computational algorithms that make up the NLCT for the segmentation of the mammary tumor. In this figure, the breast magnetic resonance data matches with the dataset described in the 2.1 section of this paper. The other elements shown in Figure 1 will be explained in the sections 2.2.1 and 2.2.2.

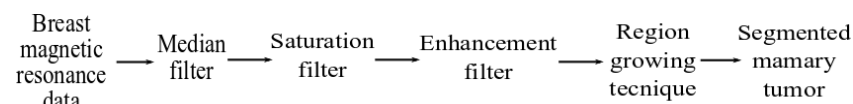


Figure 1. Block diagram of the proposed strategy.

2.2.1. Pre-processing. The main steps of this stage are: (i) Getting a median image (M_I) processing each original image (O_I) with a median filter [10]. The role of this filter is to address the noise present in the images. The tuning parameter of this filter is the size of the neighborhood. (ii) Arithmetic images. A saturated image (S_I) is obtained using the arithmetic addition of O_I and M_I ; whereas an enhanced image (I_R) is calculated by the absolute value of the arithmetic subtraction of $2 S_I$ and M_I .

2.2.2. Segmentation. In this stage the region growing (RG) technique is applied. The RG partitions an image (f) into regions (R_i) whose voxels are connected according to certain predefined criteria based on connectivity and similarity of the image. The RG needs a seed voxel into an initial neighborhood (I_v) [11]. The mathematical model that governs the RG algorithm is given by Equation (1).

$$|f(i, j, k) - \mu_{R_i}| < m\sigma_{R_i}, \quad (1)$$

being: $f(i, j, k)$ the gray levels of I_v , μ_{R_i} the average gray levels of a I_v of arbitrary shape and size, m an arbitrary scalar and σ_{R_i} the standard deviation of an arbitrary neighborhood of I_v . The Equation (1) represents the most popular predefined criterion due its simplicity and effectiveness. In this point, it is necessary to notice that the RG tuning parameters are the initial neighborhood size (r) and k parameter that controls the amplitude of the range of intensities considered to accept or reject a voxel in a region. Such parameters must undergo a tuning process.

During the tuning process, the breast cancer or mammary tumor segmented is compared with the manual segmentation traced by a mastologist. The D_s is used in order to estimate the difference or matching between these structures [12].

3. Results

First, we present qualitative results using original and preprocessed images in two-dimensional (2D) and 3D views. Then the quantitative results are shown considering mainly the Dice score and optimal parameters obtained by the algorithms present in the proposed NLCT.

3.1. Qualitative results

Figure 2 shows a 2D view of both the original image and the processed images after applying the proposed technique to the database considered. In Figure 2, we can observe the effects generated by filter bank application. A qualitative analysis reveals that the considered filters generated images of high quality reducing the noise and producing a high contrast between the anatomical structures.

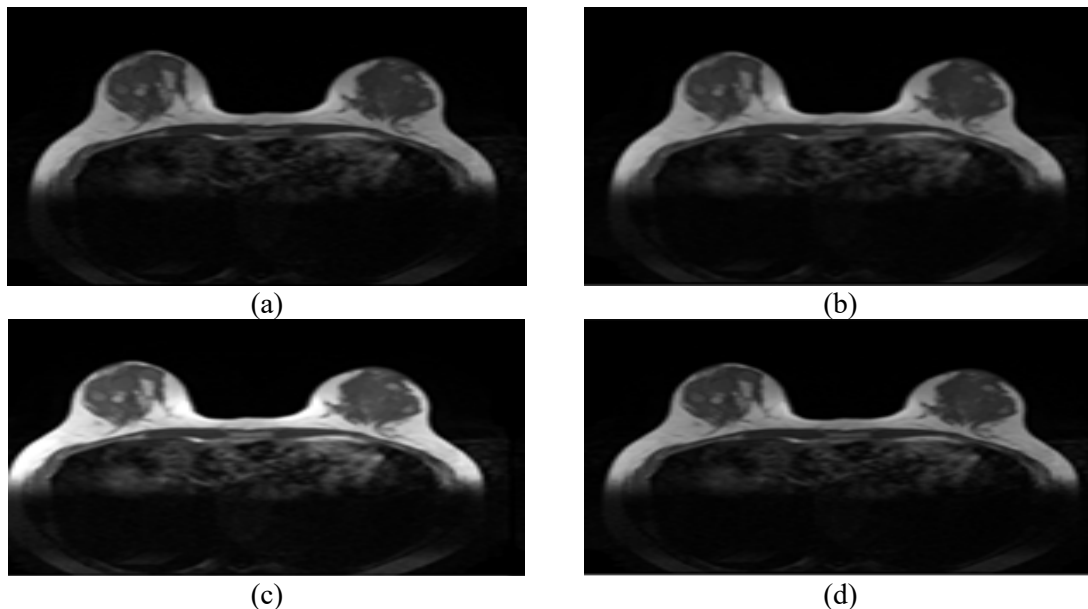


Figure 2. Preprocessing stage results; (a) original image, (b) median image, (c) saturation image, (d) enhancement image.

In Figure 2(b), we can see the effect of the median filter on the original image. Due to the statistical concept of median, a preservation of the edges is observed and an image with less noise is generated. In addition, the Figure 2(c) is a genuine representation of the saturation process that translates into the production of an image with gray levels that on average are of greater intensity than those present in the median image. Finally, in Figure 2(d), the enhancement technique generates an image in which the

imperfections of the original image have been minimized and as a consequence the quality of the information present in the anatomical structures related to the mammary gland is raised.

On the other hand, Figure 3 illustrates the results of the segmentation process developed using region growing technique. In this figure, we can observe an excellent representation of segmented mammary SOL morphology, in both 2D and 3D views.

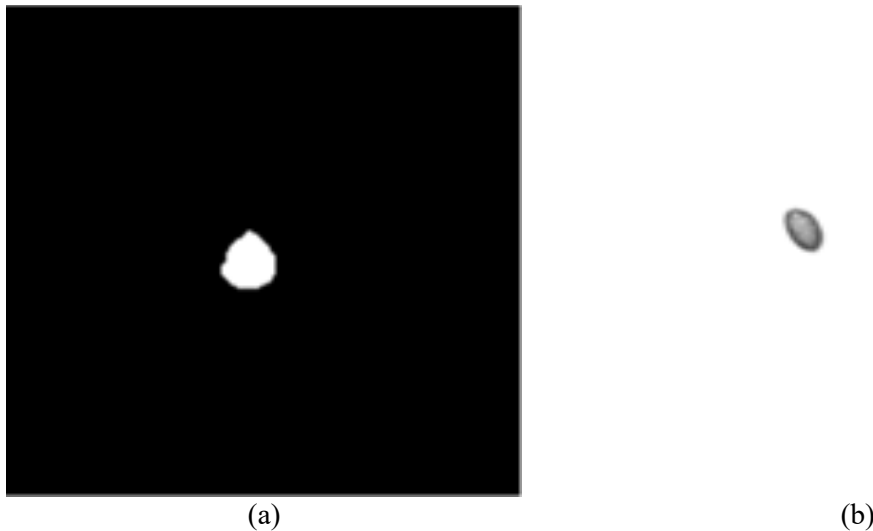


Figure 3. SOL segmented: (a) 2D view, (b) 3D view.

3.2. Quantitative results

When the tuning process was performed the mammary tumor was characterized considering its volume. So, the volume occupied by the automatically segmented breast SOL was 0.27 cm^3 ; while the volume, reported by the clinical expert, (obtained considering the manual segmentation) was 0.29 cm^3 .

The percentage relative error, considering these volumes, was 6.89% and the maximum Ds generated was 0.92. These results allowed establishing the optimal parameters of the computational algorithms that make up the proposed technique. They were: a) Median filter: the size of the kernel was corresponding with $(5 \times 5 \times 1)$. b) Region growing: $r = 1$ and $k = 1.1$.

Additionally, the Table 1 shows comparative information about the Dice score obtained both in this paper and in others researches, reported in the specialized literature.

Here, it is necessary pointed that the Ds is a metric with values between zero and 1. This metric is better when its value is closest to 1 [12]. In a medical image segmentation context, this means that the manual segmentation and the automatic one matching when the Ds is 1 and they no matching at all when the Ds is zero. In this sense, normally, values of Ds over 0.75 are okay, in the medical routine.

Table 1. Comparison using Dice score values for breast cancer segmentation.

Authors	Technique	Dice score
Sing, <i>et. al.</i> [6]	CNN	0.94
Dhungel, <i>et. al.</i> [7]	Belief networks	0.89
Zhu, <i>et. al.</i> [8]	Fully convolutional networks	0.97
Su, <i>et. al.</i> [9]	fCNN	0.85
Vargas, <i>et. al.</i> (Our technique)	NLCT	0.92

The information analysis presented in Table 1, let us to affirm that NLCT is outperform by the results reported by Sing, *et. al.* [6] and Zhu, *et. al.* [8]; whereas the computational technique proposes in this paper generated a higher value for the Ds than that reported by Dhungel, *et. al.* [7] and Su, *et. al.* [9].

It is important to notice that the techniques mentioned in Table 1 are based on smart operators that belong to the deep learning context. According with the literature, these techniques exhibit an excessive computational time during the training stage; while our technique is very efficient and let us obtain results with a similar precision that the deep learning techniques when it is intend performing the mammary tumor segmentation.

4. Conclusions

A semi-automatic technique available for detecting a SOL, type breast cancer, in a precise and efficient manner, has been presented. This technique was based in the application of median, saturation and enhancement filters in order to address the noise problem and the region growing technique for generating the 3D mammary tumor morphology, presents in magnetic resonance images.

The three-dimensional representation of this type of breast cancer is useful for the detection and monitoring of mammary diseases; as well as for the planning of medical treatments and clinical-surgical procedures linked to this pathology.

On the other hand, it is expected that the segmentation generated by the proposed method can be useful to promote, deepen and potentiate the study of the real anatomy of the structures linked to the mammary tumors.

In the immediate future it is planned to validate the proposed technique with a significant number of databases in order to estimate the robustness of the aforementioned technique.

References

- [1] Latarjet M and Ruiz A 2004 *Anatomía humana* (Barcelona: Médica Panamericana)
- [2] Bland K and Copeland E 2007 *La mama: manejo multidisciplinario de las enfermedades benignas y malignas* (Barcelona: Panamericana)
- [3] Siegel R, Miller K and Jemal A 2017 Cancer statistics *CA: A Cancer Journal for Clinicians* **67(1)** 7
- [4] Scholefield J, Duncan J and Rogers K 2014 Review of hospital experience of breast abscesses *British Journal of Surgery* **74** 469
- [5] Sing A and Gupta B 2015 A novel approach for breast cancer detection and segmentation in a mammogram *Procedia Computer Science* **54** 676
- [6] Singh V, Romani S, Rashwan H, Akram F, Pandey N, Sarker M 2018 Conditional generative adversarial and convolutional networks for x-ray breast mass segmentation and shape classification *21st International Conference on Medical Image Computing and Computer Assisted Intervention MICCAI 2018* (Granada) vol 11071 (Cham: Springer) p 833
- [7] Dhungel N, Carneiro G and Bradley A 2015 Tree re-weighted belief propagation using deep learning potentials for mass segmentation from mammograms *12th International Symposium on Biomedical Imaging (ISBI)* (New York: IEEE) p 760
- [8] Zhu W, Xiang X, Tran T, Hager G and Xie X 2018 Adversarial deep structured nets for mass segmentation from mammograms *15th International Symposium on Biomedical Imaging (ISBI)* (Washington: IEEE) p 847
- [9] Su H, Liu F, Xie Y, Xing F, Meyyappan S and Yang L 2015 Region segmentation in histopathological breast cancer images using deep convolutional neural network. *12th International Symposium on Biomedical Imaging (ISBI)* (New York: IEEE) p 55
- [10] Pratt W 2007 *Digital image processing* (New York: John Wiley & Sons Inc)
- [11] Huérfano Y, Vera M, Mar A and Bravo A 2019 Integrating a gradient-based difference operator with machine learning techniques in right heart segmentation *Journal of Physics: Conference Series* **1160** 012003
- [12] Dice L 1945 Measures of the amount of ecologic association between species *Ecology* **26(3)** 29