# Otsu's Thresholding for Semi-Automatic Segmentation of Breast Lesions in Digital Mammograms

Moustapha Mohamed Saleck[1]
LAROSERI Laboratory, Computer Sciences Department
Faculty of Sciences, University of Chouaïb Doukkali
EL Jadida, Morocco

M. H. Ould Mohamed Dyla[2]
Computer Sciences Department
IUP, University of Nouakchott
Nouakchott, Mauritania

EL Benany Mohamed Mahmoud[3]
Department of Mathematics and Computer Science
FST, University of Nouakchott
Nouakchott, Mauritania

Mohamed Rmili[4]
Computer Sciences Department
Faculty of Sciences, University of Chouaïb Doukkali
EL Jadida, Morocco

***Abstract*—In Maghreb countries, breast cancer considered one of the leading causes of mortality between females. A screening mammogram is a method of taking low energy level x-ray images of the human breast to identify the early symptoms of breast cancer. The shape and contour of the lesion in digitized mammograms are two effective features that allow the radiologists to distinguish between benign and malignant tumors. We propose in this paper a new approach based on Otsu's thresholding method for semi-automatic extraction of lesion boundaries from mammogram images. This approach attempts to find the best threshold value where the weighted variance between the lesion and normal tissue pixels is the least. In the first step, the median filter is used for removing noise within the region of interest (ROI). In the second step, a global threshold decrement was started in order to get the proper range of pixels in which the breast lesion could be segmented by Otsu's thresholding method with high accuracy. The technique of mathematical morphology, especially opening operation is used in this work for removing small objects from the ROI while preserving the shape and size of larger objects that represent the tumors. We evaluated our proposal using 21 images obtained from Mini-MIAS database. Experimental results show that our proposal achieves better results than many previously explored methods.**

***Keywords—Tumor detection; lesion segmentation; mammogram images; Otsu's thresholding***

## I. Introduction

According to the statistics published in 2020 by World Health Organization (WHO) [1] Breast cancer is classified as one of the most common cancer and a leading cause of deaths among women worldwide. The study given by WHO show that 2.3 million women about the world were subjected to diagnosis of breast cancer in 2020, and almost 29.1% of this rate died out (685 000 deaths globally). Mortality rates for breast cancer are increasing at fast and no way to treat this disease yet except early detection that can help in increasing the survival rate. Different modalities of medical imaging have been used as screening tools for detecting and diagnosis of breast cancer, such as mammography, ultrasound, magnetic resonance imaging (MRI), nuclear medicine imaging, optical imaging, and breast microwave imaging [2]. Mammography is considered as one of the most commonly used tests for detecting breast cancer at early stages [3], it can often help find breast cancer early and reveal different abnormalities before any symptoms appear. The shape and contour of mass represent one of the most important information in analyze of mammograms. Breast mass segmentation has a key role in determining the nature of lesion since the mass having regular shapes have a high probability of being benign and the mass having irregular shapes have a high probability of being malignant. There are many challenges to detect mass contour in mammograms due to several factor including: normal breast tissues seemed to be similar to lesions, low contrast, fuzzy nature of the boundaries, complicated structured background.

In the present study, we introduce a new approach for breast masses segmentation in mammographic images, in this approach we apply Otsu's method in appropriate range of pixels limited by the maximum value of intensity and an optimal threshold where the output of Ostu is made up of two clusters one of them represents the lesion with high contour accuracy. Our proposal is titled semiautomatic because the regions of interest (ROI) are selected manually by expert breast radiologist.

The scheme proposed in this study combines the median filter, Otsu's thresholding and mathematical morphology (opening operation). The remainder of this paper is organized as follows: Section II presents related state-of-the-art works; Section III presents the proposed exploration scheme of breast lesion boundaries from digital mammograms. Section IV shows the experimental results. In Section V we discuss about the results. Finally, the conclusions of this work are presented in Section VI.

## II. Related Work

The success of lesion contour detection is directly associated with the choice of the measures and methods. Various approaches have been proposed in the literature for mass segmentation in mammographic images. N.Soliman et al. [4] developed a framework for processing of mammogram images, in their work the authors have used 2D median filter to remove digitization noise from images and morphological operations to remove artifacts, they have used also a fuzzy enhancement technique for contrast enhancement and Otsu's multiple thresholding method for mammogram segmentation. Wessam M. Salama et al. [5] proposed a new framework for breast cancer image segmentation and classification. InceptionV3, DenseNet121, ResNet50, VGG16 and Mobile-NetV2 models are utilized to classify Mammographic Image, then the modified segmentation of the U-Net model is used for the segmentation process. V. Punithavathi et al. [6] proposed an approach based on Optimized Kernel Fuzzy Clustering Algorithm (OKFCA) to determine the cancer portions in mammogram images, After applying the Hybrid Denoising Filter (HDF) Algorithm in preprocessing, the proposed OKFCA is carried out to find out the cancer segment of mammogram image. J. Anitha et al. [7] presented a new approach based on the global adaptive thresholding to locate the suspicious regions in mammogram images. This optimal global threshold (Dual Stage Adaptive Thresholding (DuSAT)) is selected adaptively by maximizing between-class standard deviation, calculated from the gray level of the preprocessed image through the histogram peak analysis (HPA) of the entire image. Damian Valdés-Santiago et al [8] proposed two algorithms for mass boundaries extraction from mammogram images : a lesion segmentation approach based on a Fuzzy C–means modification using image histogram, and a selection criteria to choose candidate lesions that will serve as input to a classifier based on a binary decision tree. H Azary et al. [9] proposed a semi-supervised technique for mass segmentation in mammogram images in which the authors extracted the pixel information such as : the static, gray level run length matrix features and Fisher discriminant analysis (FDA) to use it in the process of classification. After that, they used a co-training algorithm based on support vector machine and Bayes classifiers for tumor segmentation. In [10] Mohammed Y. Kamil et al. applied two algorithms of the clustering approach were applied to three images from Mini-MIAS Database for determining the boundaries of the tumor. the first is the K-means method and the second is the C-means method, in addition, the lazy snapping algorithm is applied to improve the performance of segmentation of suspect area. The results showed that the second algorithm of clustering is better than the first algorithm in terms of accuracy. In [11] M. Ramli et al. suggested a hybrid method of tumor boundary detection in mammogram images. After noise suppression by using median filter method, the Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique have used for image contrast enhancement. in the first stage of segmentation, the watershed transform technique is applied to extract the original region of interest (ROI), and then, the authors employed the region growing algorithm in determining the tumor's boundaries. R. S. C. Boss, et al. [12] extracted 14 Haralick texture features from mammogram image using GrayLevel Co-occurrence Matrix (GLCM) for different angles with distance d = 1. Fuzzy c-means and K-means algorithms are used to classify texture features in order to segment the region of interests (ROI) for further classification. T.Sadad et al. [13] employed the cascading of Fuzzy C-Means (FCM), morphological operations and region-growing (RG) method for extracting the tumor located in mammograms, the Local Binary Pattern Gray-Level Co-occurrence Matrix (LBP-GLCM) and Local Phase Quantization (LPQ) are also been used for feature extraction. S. S. Ittannavar et al. [14] developed a new multiobjective optimization technique for breast lesions segmentation in mammogram images. The developed model contains three phases: image collection from Digital Database for Screening Mammography (DDSM) and Mammographic Image Analysis Society (MIAS), image enhancing using Contrast-Limited Adaptive Histogram Equalization (CLAHE) techniques, and finally electromagnetism-like (EML) optimization technique is used to detect noncancer and cancer portions on mammograms. In [15] S.H Suradi et al. used Fuzzy Anisotropic Diffusion Histogram Equalization Contrast Adaptive Limited to enhance the breast lesions by reducing the image noise. Then, a Multilevel Otsu Thresholding is applied to detect breast lesions using the e region of interest tool at different intensity levels. T.L.V.N.Swetha et al. [16] developed an approach based on tow combined methods for tumor edges detection, the first is Hybrid image segmentation based on fast sweeping algorithm and dual front evolution with laplacian or gradient, the second is Otsu's thresholding with 10 threshold levels. A.K.Khan et al. [17] proposed an approach based on improved Otsu method and discrete wavelet transform (DWT) for breast lesion detection in mammograms, in their work the adaptive median filtering and adaptive histogram equalization were used in preprocessing step. In [18] M.M.Saleck et al. developed a semi-automatic segmentation of breast masses on mammogram images using the algorithm of Fuzzy C-Means where the number of clusters is known in advance without estimation, the authors play on the set of pixels that subject to clustering by decrement global threshold to obtain the best results of segmentation. The major disadvantage of this approach is the long execution time that it takes, the present work overcome this drawback by providing another approach based on Otsu's thresholding with less execution time.

## III. Materials and Methods

In this part of paper, we explain the techniques that were used in this study for the detection of lesions boundaries on a mammogram. The methodology comprises the following stages: Image preprocessing. Starts the process of decrement a global threshold and applying Otsu method in each step of decrement operation on the set of selected pixels (input_pixels) that exist between the maximum intensity value and the global threshold. Identify the best value of global threshold for determining the optimal segmentation by applying morphological opening to suppress undesirable objects.

Fig. 1 shows a schematic diagram of the proposed method.

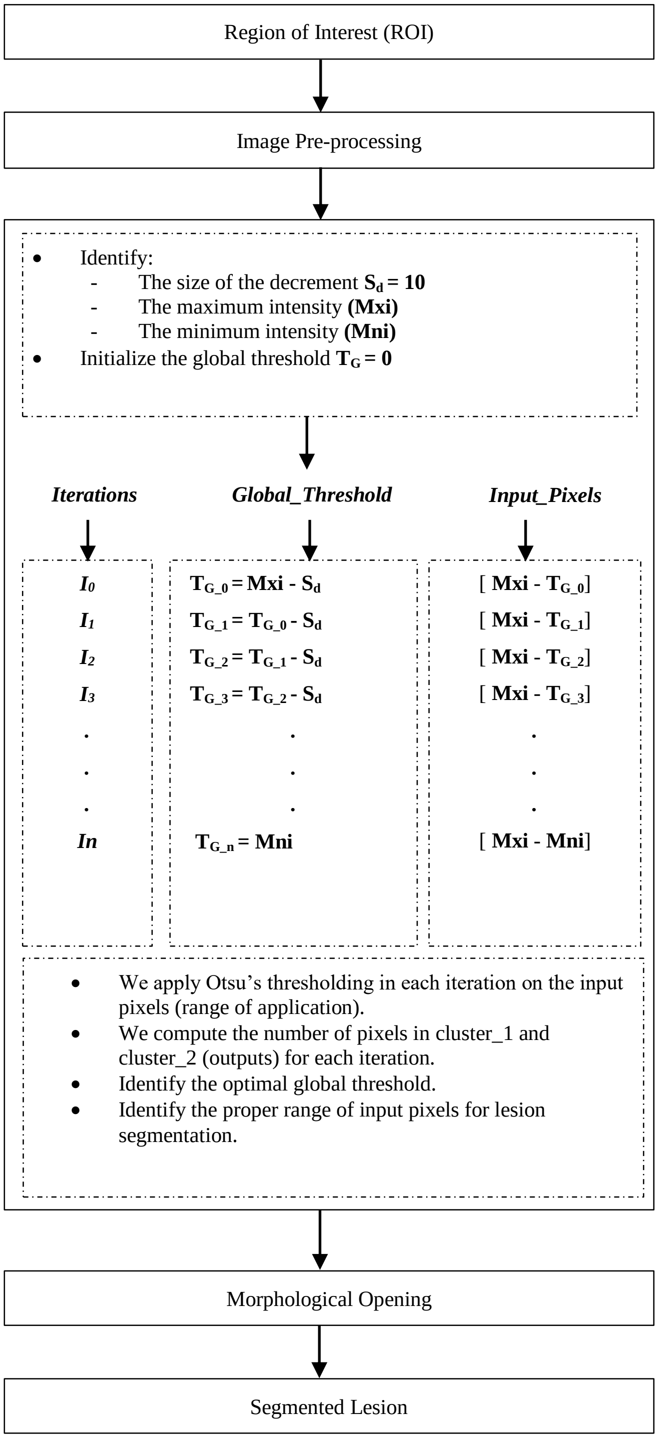



Fig. 1. Block Diagram of the Proposed Method.

## A. Region of Intersect Selection

The breast mammography images used to test our proposed methods were extracted from the Mammographic Image Analysis Mini-Mammographic Database (Mini-MIAS) [19]. The dataset includes 322 digital mammograms, the size of each mammogram from the database was reduced to become $1024 \times 1024$, with 8-bits grey scale level and a spatial resolution of 200-micron pixel edge. The ground truth (GT) of these mammograms have been manually extracted by a radiologist and all abnormalities have been identified and classified. The Region of Interest (ROI) represent the place where abnormalities are identified. In this paper, we use the region of interest with a size of 174 x174 pixels, the value 174 is chosen in consultation with the radiologist because it is the radius of the largest mass present in the database [20].

## B. Image Pre-processing

Preprocessing steps are very necessary and should be applied before any image-processing technique to ensure a high level of accuracy without any influences from background [21]. Digital mammograms are medical images that are difficult to be interpreted due to the dynamics of intensity and noise appears in images provided by different patients. The basic enhancement required in digital mammograms is denoising [22]. A median filter is a nonlinear filtering technique, it is very effective at removing impulse noise, pepper noise and Gaussian noise. Its strength lies in its ability to keep the sharpness of the image at the time of enhancement. Potency of median filter depends on the size of window [23]. In this work, we applied a median filter with a simple sliding-window of size 3x3 in order to provide smart result in proposed algorithms.

## C. Morphological Operations

Morphological Operations is the set of image processing operations that follows the goal of eliminating all the imperfections and maintaining image structure. These techniques include opening operation which is a process that applies erosion on an input image and then dilates the eroded image using the same kernel in both operations. The morphological opening could be used for removing small objects and thin lines in the segmentation results. In this work, we apply morphological opening to retain only the biggest region that represents the tumor with accuracy.

## D. Breast Mass Segmentation by Otsu's Thresholding

Otsu's segmentation is a non-parametric and unsupervised technique proposed by Nobuyuki Otsu [24]. It is an automatic threshold selection method that maximizes the between-class variance in order to segment the image into classes using optimum threshold values. To threshold a given image presented in L gray levels, $[0, 1, 2, \ldots, L-1]$ into two classes $C_1$ and $C_2$, we select a threshold k, $0 < K < L-1$. Where the range $[0, K]$ represent the intensity of pixels for the first class ($C_1$), while the second class ($C_2$) is presented by the pixels that have intensity values within the range $[k+1, L-1]$.

$P_1(k)$, represent the probability that a pixel is assigned to first class ($C_1$).

$$P_1(k) = \sum_{i=0}^{k} P_i \tag{1}$$

$P_2(k)$, represent the probability that a pixel is assigned to second class ($C_2$).

$$P_2(k) = \sum_{i=k+1}^{L-1} P_i \tag{2}$$

The mean intensity values of classes $C_1$ and $C_2$ are defined as:

$$m_1(k) = \sum_{i=0}^{k} \frac{i\,P_i}{P_1(k)} \quad (3)$$

$$m_2(k) = \sum_{i=k+1}^{L-1} \frac{i\,P_i}{P_2(k)} \quad (4)$$

Otsu method tries to minimize the weighted within-class variance defined as:

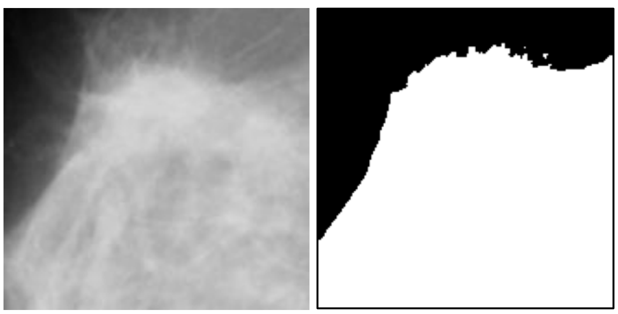
$$\sigma_\omega^2(k) = m_1(k)\sigma_1^2(k) + m_2(k)\sigma_2^2(k) \quad (5)$$

The variances for classes $C_1$ and $C_2$ are defined as:

$$\sigma_1^2(k) = \sum_{i=0}^{k} [i - m_1(k)\,]^2 \frac{iP_i}{P_1(k)} \quad (6)$$

$$\sigma_2^2(k) = \sum_{i=k+1}^{L-1} [i - m_2(k)\,]^2 \frac{iP_i}{P_2(k)} \quad (7)$$

It's difficult to extract the boundaries of masses from mammogram images by using the classic Otsu thresholding technique only except in rare cases, due to the low difference between normal and abnormal tissue in mammograms. Fig. 2 shows the result of segmentation by using the classic Otsu thresholding.



(a) (b)

Fig. 2. Lesion Segmentation using Classic Otsu's Thresholding: (a) Original Image (mdb_95 from MIAS). (b) Result of Segmentation (mdb_95).

The fuzzy nature of the mammographic images and the low contrast due to masses obscuration by tissue overlap make the automatic process of lesion boundaries extraction very difficult. To overcome this limitation, we propose in this paper a new approach based on Otsu thresholding where the sets of pixels that will subject to clustering by Otsu thresholding are limited by two parameters:

- The first limit (upper limit) of the range of pixels is the maximum value of intensity, because the suspicious lesions in mammogram image having a high-intensity values compared to other regions.
- The second limit (lower limit) of the range is a global threshold, where all pixels in the ROI with intensities below this threshold value are turned off (will not be subject to process of thresholding by Otsu methos).

To threshold a given set of pixels within the range [Mxi – $T_G$] into to clusters $C_1$ and $C_2$ by Otsu's thresholding where:

- Mxi is the maximum of intensity in the ROI.
- $T_G$ is a global threshold.

We select a threshold k, $T_G < K < L-1$, where:

- $[T_G, K]$ represent the intensity of pixels for the first cluster $C_1$.
- $[K+1, Mxi-1]$ represent the intensity of pixels for the second cluster $C_2$.
- $P_1(k)$, represent the probability that a pixel is assigned to first class ($C_1$).

$$P_1(k) = \sum_{i=T_G}^{k} P_i \quad (8)$$

- $P_2(k)$, represent the probability that a pixel is assigned to second class ($C_2$).

$$P_2(k) = \sum_{i=k+1}^{Mxi-1} P_i \quad (9)$$

- The mean intensity values of $C_1$ and $C_2$ are defined as:

$$m_1(k) = \sum_{i=T_G}^{k} \frac{i\,P_i}{P_1(k)} \quad (10)$$

$$m_2(k) = \sum_{i=k+1}^{Mxi-1} \frac{i\,P_i}{P_2(k)} \quad (11)$$

- The variances for classes $C_1$ and $C_2$ are defined as:

$$\sigma_1^2(k) = \sum_{i=T_G}^{k} [i - m_1(k)\,]^2 \frac{iP_i}{P_1(k)} \quad (12)$$

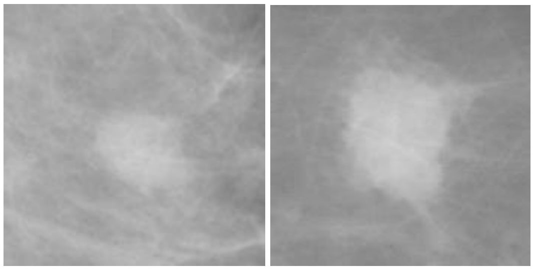
$$\sigma_2^2(k) = \sum_{i=k+1}^{Mxi-1} [i - m_2(k)\,]^2 \frac{iP_i}{P_2(k)} \quad (13)$$

Run through the full range of $k$ values [ $T_G$ - $Mxi$] and pick the value that minimizes $\sigma_\omega^2(k)$ defined in eq. (5).

In this approach, we start the decrement of the global threshold ($T_G$) from the maximum intensity($Mxi$) in ROI until the minimum value of intensity ($Mni$) in ROI with a step size $S_d$ =10. Choosing a small decrement step size leads to very slow execution time, however, takes a large decrement step value effects on the segmentation accuracy. To balance between these two points and after many tests, we have deduced that $S_d$ = 10 is the optimal value of the decrement step.

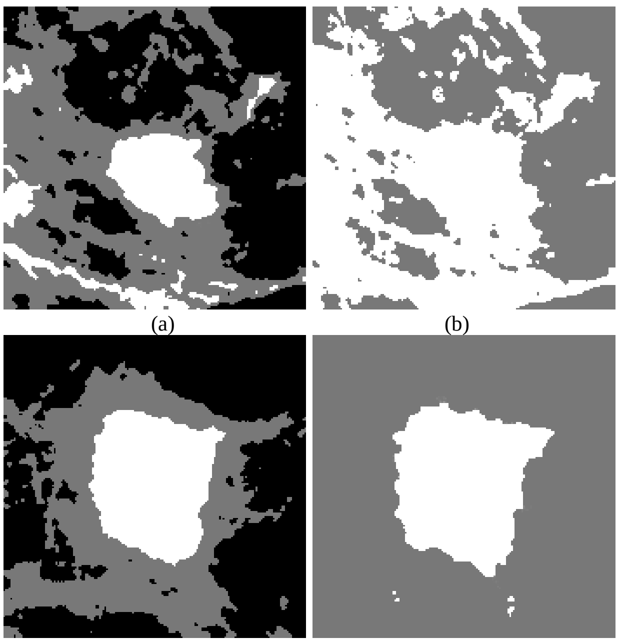
Fig. 3 shows the original images from MIAS. Fig. 4 represents the application of the proposed Otsu method on different sets of pixels where each one of these sets exists within a range limited by the maximum intensity and global threshold.

The optimal global threshold (the second limit of the range of input-pixels) is getting by tracking the changes in the number of pixels that belong to each output-cluster during the process of increase in the set of pixels that subject to clustering by Otsu's thresholding. Tables I and II shows the evolution in the number of pixels that belongs to cluster_1 and cluster_2 at each iteration $t_i$, also the different values of global thresholds and Otsu thresholds for mdb_10 and mdb_134.



(a) (b)

Fig. 3. Original Images: (a) mdb_10 from MIAS (Max Intensity = 206, Min Intensity = 118). (b) mdb_134 from MIAS(Max Intensity = 208, Min Intensity = 119).



(a) (b)

(c) (d)

Fig. 4. Application of the Proposed Otsu Method in different Ranges of Pixels. (a) (b): mdb_10 from MIAS. (c) (d): mdb_134 from MIAS. White: Cluster_1. Dark Gray: Cluster_2. Black: Outside the Range (Not Subject to otsu thresholding).

The evolution curves in the following figures (Fig. 5 and Fig. 6) illustrates the changes in the number of pixels of clusters that happen at each iteration $t_i$.

TABLE I. EVOLUTION OF THE NUMBER OF PIXELS IN CLUSTER 1 AND CLUSTER 2 FOR IMAGE MDB 10 FROM MIAS

| **Image: mdb_10 from MIAS Database**<br>**The maximum value of intensity (Mxi) = 206**<br>**The minimum value of intensity (Mni) = 118** | | | | |
|---|---|---|---|---|
| ***Range of pixels*** | ***Number of pixels in cluster_1*** | ***Number of pixels in cluster_2*** | ***Global threshold ($T_G$)*** | ***Otsu threshold*** |
| $t_1$ : [206 - 196] | 176 | 448 | 196 | 200 |
| $t_2$ : [206 - 186] | 883 | 1124 | 186 | 194 |
| $t_3$ : [206 - 176] | 1685 | 4320 | 176 | 188 |
| $t_4$ : [206 - 166] | 3875 | 13288 | 166 | 180 |
| $t_5$ : [206 - 156] | 6637 | 19369 | 156 | 177 |
| $t_6$ : [206 - 146] | 6805 | 22768 | 146 | 176 |
| $t_7$ : [206 - 136] | 11734 | 18119 | 136 | 170 |
| $t_8$ : [206 - 126] | 15834 | 14359 | 126 | 167 |
| $t_9$ : [206 - 118] | 15834 | 14442 | 118 | 167 |

TABLE II. EVOLUTION OF THE NUMBER OF PIXELS IN CLUSTER 1 AND CLUSTER 2 FOR IMAGE MDB 134 FROM MIAS

| **Image: mdb_134 from MIAS Database**<br>**The maximum value of intensity (Mxi) = 208**<br>**The minimum value of intensity (Mni) = 119** | | | | |
|---|---|---|---|---|
| ***Range of pixels*** | ***Number of pixels in cluster_1*** | ***Number of pixels in cluster_2*** | ***Global threshold ($T_G$)*** | ***Otsu threshold*** |
| $t_1$ : [208 - 199] | 270 | 554 | 198 | 202 |
| $t_2$ : [208 - 188] | 1379 | 1777 | 188 | 196 |
| $t_3$ : [208 - 178] | 2324 | 2043 | 178 | 192 |
| $t_4$ : [208 - 168] | 3441 | 2068 | 168 | 186 |
| $t_5$ : [208 - 158] | 4146 | 3661 | 158 | 180 |
| $t_6$ : [208 - 148] | 4918 | 10438 | 148 | 173 |
| $t_7$ : [208 - 138] | 5361 | 21398 | 138 | 169 |
| $t_8$ : [208 - 128] | 5753 | 24266 | 128 | 166 |
| $t_9$ : [208 - 119] | 6060 | 24216 | 119 | 164 |

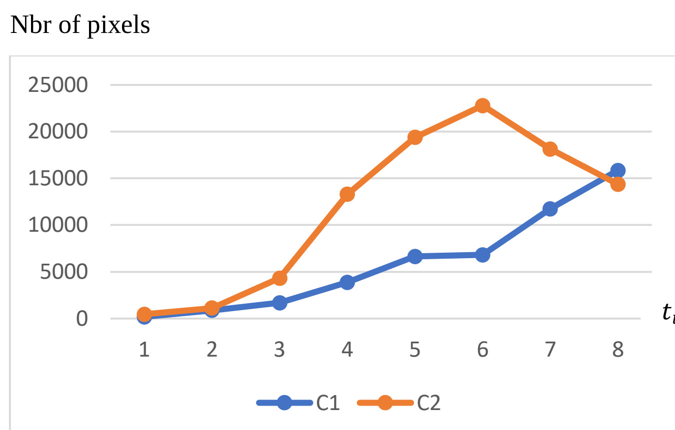



Fig. 5. Evolution of Cluster 1 and Cluster 2 for mdb 10.

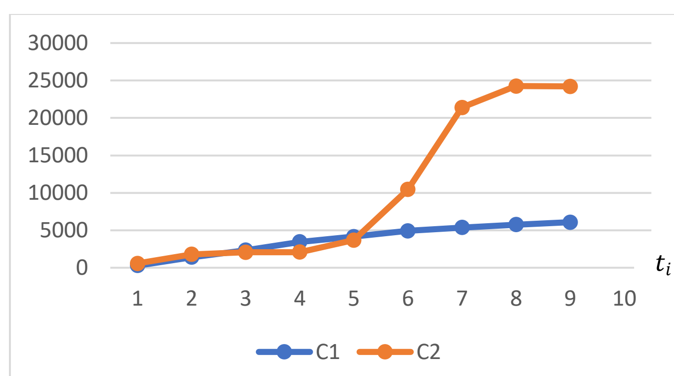



Fig. 6. Evolution of Cluster 1 and Cluster 2 for mdb 134.

After tracing the evolutionary changes in the number of pixels for both clusters (C1 and C2) on 22 images tested in this study, we can distinguish two different sorts of results:

- The first one represents the majority of the cases; this one is characterized by an increase in the number of pixels of cluster 1 and cluster 2 followed by an abrupt decrease in cluster 2. The optimal global threshold for this kind of case is the value that happens an abrupt decrease in cluster 2. Ex: Fig. 5 (mdb 10) the best value of the global threshold is $T_G$ = 146 at iteration t=6, therefore, the appropriate range of pixels that allow us to get two clusters where the cluster 1 represent the lesion with accuracy in this example is [206 - 146].
- The second is characterized by an increase continues in cluster 2, those cases are rare. The optimal global threshold for this kind is the minimum value of intensity (Mni) in the region of interest (ROI). **Ex:** Fig. 6 (mdb 134) the best value of the global threshold is the minimum intensity $T_G$ = 119.

After finding the suitable range of pixels that can generate high accuracy of lesion boundaries after applying the proposed Otsu method, we apply morphological operations to remove all defects and preserve the region having the highest intensity in cluster 1 that represents the lesion.

## IV. Experimental Results

In this section, we present the experimental results for breast mass segmentation in mammogram images using the proposed method. A testing data set of 21 images taken from mini-MIAS database of mammograms were used in this study to test and evaluate the performance of the proposed approach. Three experienced radiologists have intervened for delineating manually the lesions margins. The obtained results in Fig. 7 shows that lesion border extracted by the proposed algorithm approximately follows the lesion contour marked by the radiologists.

To evaluate the efficiency of the proposed algorithm, four performance evaluation metrics were adopted in this paper, such as: overlap, sensitivity, specificity and accuracy [25].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (14)$$

$$\text{Overlap} = \frac{TP}{TP+FP+FN} \times 100 \quad (15)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100 \quad (16)$$

$$\text{Specificity} = \frac{TN}{FP+FN} \times 100 \quad (17)$$

Table III displays the results of metrics of lesion segmentation obtained for measurement the performance of the proposed approach. Table IV presents the comparison with other techniques.

The proposed method is implemented on Python 3.9.5, Pycharm community edition 2021.2.2. The computer used in this work is Dell PC with Processor Intel(R) Core (TM) i5-5300U CPU 2.30GHz (4 CPUs), and 8G Ram.

The average processing time required for completing the process of segmentation using the proposed algorithm is 1.91 s, the runtime time for this approach is less 2 times than the segmentation of breast lesions using Fuzzy c-means algorithm proposed in [18] (Fig. 8).

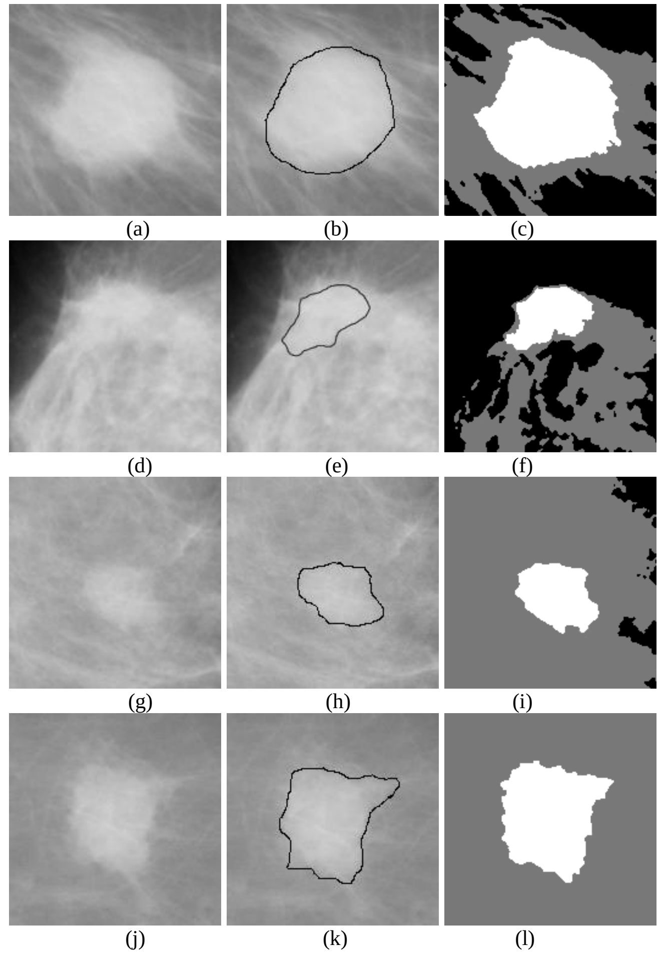



Fig. 7. (a)(d)(g)(j) The Original Mammograms. (b)(e)(h)(k) Lesions Outlines Marked by Radiologist. (c)(f)(i)(l) Lesions Extracted by the Proposed Algorithm.

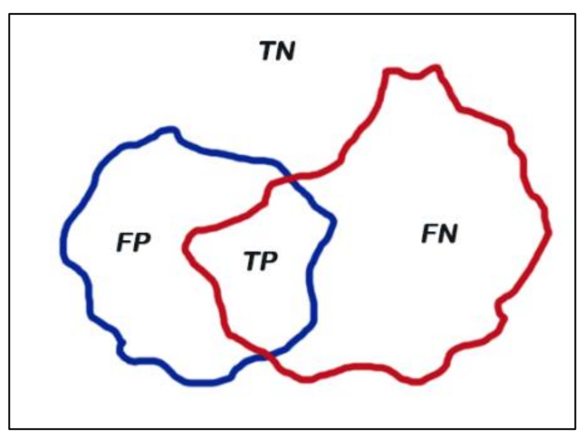



Fig. 8. The Red Contour: Lesion Outlined by a Radiologist. The Blue Contour: Lesion Outlined by a System. TP: True Positives. TN: True Negatives. FP: False Positives. FN: False Negatives.

TABLE III. PERFORMANCE RESULTS OF SEGMENTATION

| Number of lesions | 21 images from mini-MIAS | | | |
|---|---|---|---|---|
| | ***Accuracy*** | ***Overlap*** | ***Sensitivity*** | ***Specificity*** |
| 22 | 95.06 % | 80.92 % | 97.16 % | 73.41 % |

TABLE IV. COMPARISON WITH OTHER TECHNIQUES

| Methods | ***Overlap*** | ***Accuracy*** | ***Sensitivity*** | ***Specificity*** |
|---|---|---|---|---|
| Proposed method | 80.92 % | 95.06 % | 96.16 % | 73.41 % |
| Watershed and region growing : [26] | 80.3 % | 91.5 % | 91 % | 94.35 % |
| Fuzzy c-means and K-means : [10] | -- | 91.18 % | -- | -- |
| Deep learning : [27] | -- | 98 % | -- | -- |
| Region growing : [28] | 79 % | 91 % | 83 % | 97 % |

## V. DISCUSSION

This study presents a new approach for extracting masses from ROI of digital mammogram images, aiming to assist the radiologist in the identification of the lesion. This approach is based on increasing the set of pixels that subject to clustering by decrement a global thresholding. This processing allows to test the different values of global thresholds in order to obtain the best value. The aim is to select as input the meaningful pixels that can produce in output a clearly delineated lesion after applying Otsu thresholding and morphological operations. In comparing the results of segmentation for mdb_95 from Mini-MIAS database using classic Otsu thresholding illustrated in Fig. 2 and the results of segmentation for the same image showed in Fig. 7(f), we can deduce the efficiency of the proposed method. The strength of this method lies in its ability to eliminate the set of pixels that can have negative effects on the process of segmentation by choosing a suitable global threshold. The run-time of the proposed algorithm is considerably less than the execution time for the proposed method in [18]. This speed of execution compared to fuzzy c-means is due to the simplicity of the Otsu method in terms of algorithm complexity.

## VI. CONCLUSION

Breast cancer is the most common type of cancer among women around the world and is the second leading of death after prostate and lung cancer. We aim behind our researches, to develop new methods for helping the radiologists in diagnostic of breast cancer. In this study, we propose a new approach for breast lesion boundary segmentation for a given region of interest (ROI) in mammographic images. The proposed algorithm is an extended version of classical Otsu's technique with additional capability to dynamically change the number of input-pixels that subject to thresholding in order to get the proper set of pixels which can produce as output a segmented lesion with high accuracy. The results obtained in this work show the proposed algorithm outperforms many other methods of breast masses segmentation in performance and that it is faster than the fuzzy c-means technique.

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