

# Automatic Segmentation in Breast Thermographic Images Based on Local Pattern Variations

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**Abstract.** In order to detect any possible anomaly in the region of breast, the use of thermal images has experienced a considerable workload of research in the recent years, this due to the promising results of this technique. One of the principal tasks in this process is the segmentation of the Region of Interest (ROI), but this task is difficult, most of the proposed techniques perform a manual or semi-automatic process to extract it. In this paper, we propose an alternative technique to detect the ROI in thermal breast images. In the proposed technique, we focus on the higher temperature areas in the image. We apply local contrast enhancement, group higher temperature regions, spline cubic interpolation and statistical operations as a part of the method. The achieved results are competitive with the state of the art showing a new alternative to accomplish the automatic segmentation of thermal breast images.

**Keywords:** Automatic segmentation, Contrast enhancement, Image processing, Thermography.

## 1 Introduction

According to the World Health Organization from the last decade, cancer diseases are the second dealing cause of global death, by 2015 cancer accounted 8.8 millions of deaths. There are several types of cancer but perhaps one of the most dangerous and common is breast cancer, which has occasioned 571 000 deaths [1]. Cancer mortality can be reduced if cases are detected and treated early [1]. Breast cancer usually appears in ducts; tubes that carry milk to the nipple, and lobules; glands that produce milk. Some works have reported that the growth rate of a tumor is proportional to its temperature [17]. There are a lot of research in this field, one of the current investigations to detect anomalies in early stages is the use of digital thermal images which take into account patterns based on temperature changes.

There exist several procedures in order to diagnose breast cancer such as Mammograms, Ultrasounds, Magnetic Resonance Imaging (MRI) and others [2, 3, 4]. The mammogram is a widely used study, but the problem is the limited range of population whom are candidates (young women are not suitable), the invasive and even hurtful procedure, the expensive devices utilized, and finally it requires repeated exposure to radiation (who is nocive for human health [5]). The ultrasound and the MRI

are commonly performed as the previous step of a mammography, but in spite of its good results, none of these studies are 100% accurate, the only study that achieves that precision is the biopsy.

Infrared images do not use ionizing radiation, venous access, or other invasive procedures. The infrared image presents physiological information of normal and abnormal functioning of the vascular system, sensorial and sympathetic nervous system, and inflammatory processes [6, 7]. The combination of mammographies and thermography, allows the achievement of a high degree of specificity and sensibility on such diagnosis [8, 10]. Moreover, thermography is very useful for detecting non palpable breast cancer in earlier stages [6]. Nevertheless it has to be clear and well understood that thermography by itself cannot replace any of the other studies, it is a complement of all of them.

In the digital images analysis process, an important and difficult task to achieve is the ROI segmentation, which allows the delimitation of the data to be analyzed. In the case of thermal breast images, the ROI must include all the breast tissue and near ganglion groups since cancerous cells usually appear in the glands that produce milk and the ducts that carry it to the nipples [17]. An accurate segmentation of ROI from medical thermal images still remains as an open problem. Most authors perform semi-automatic or manual ROI extraction because it is a hard task due to inherent limitations of thermal images such as the absence of clear edges, low contrast nature and low signal to noise ratio [9].

There are various techniques presented in reviews that perform automatic segmentation [9, 11, 18]. For example Marques et al. [12] presented an automatic segmentation method which consists of image processing techniques such as thresholding, clustering, edge detection and refinement among others. Villalobos-Montiel et al. [13] used Canny edge detection with automatic threshold and symmetry inspection, besides Hough transform and Active Contours are used to provide a better approximation to the ROI. Hinojosa et al. [19] proposed the use of thresholding techniques as objective functions in evolutionary algorithms, in particular the HS (Harmony Search) algorithm provided excellent results. Ali et al. [20] used the distance between camera and patient as a relevant parameter, they assumed the ROI is always in the same region so they defined fixed regions to obtain it, but their approach fails many times due to the lack of dynamic in their method. Sathish et al. [21] have focused on shape features of the breast and polynomial curve fitting, also a statistical test is performed to evaluate the results who are competitive with the related work. Hankare et al. [22] proposed a method who performs a color space transformation from RGB to a  $L^*a^*b^*$  color space, then a k-means classification with an Euclidean distance is applied, finally the cluster with the biggest temperatures is segmented. Prakash et al. [23] presented three segmentation techniques K-Means, Fuzzy C-Means and Gaussian Mixture Model – Expectation Maximization, in this paper also the color space transformation was important to achieve good results. Sayed et al. [24] proposed a method using bio-inspired swarm techniques forming clusters looking for the most optimal, the FA (Firefly Algorithm) algorithm was the best swarm version that obtained the highest accuracy, sensitivity, precision and specificity. Mejia et al. [25] used morphological operators in order to enhance the ROI area, then thresholding and the Extended-

minima transform are performed to search neighborhoods connected who delimited the ROI region. Garduño-Ramón et al. [26] employed morphological watershed operator to help to locate a possible tumor, thresholding operations and polynomial curve fitting were also performed.

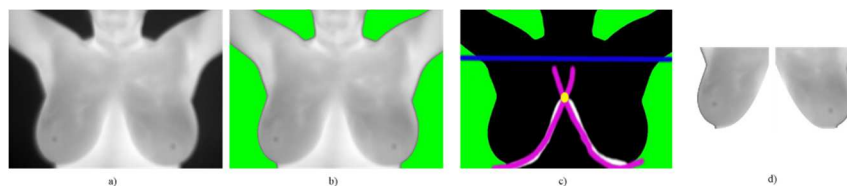
However, most techniques fail to perform a correct segmentation in images where the borders in the ROI are unclear due to the different physical characteristics of each person besides many focus only in the tumor region and not in the whole area of the breast and with this approach a common problem is the irregular shape of malignant tumors.

In this paper we present a technique that performs an automatic ROI segmentation for thermal breast images. This consists of four main stages, the first stage extracts the background from the image, Otsu's method [15] is applied; the second stage finds the bottom boundaries of the ROI, to achieve this, automatic thresholding methods are used, local contrast enhancement, clustering of regions that represent the highest temperatures and polynomial curve fitting through interpolation methods are also performed; the third stage is focused on detect the upper boundaries, statistical analysis in the area of lateral borders is applied, finally in the fourth stage the segmentation of each breast and also some correction operations are performed.

The organization of the paper is the following, in section 2 the methodology for the proposal is presented, in section 3 results and discussion are presented, finally in section 4 the conclusions are drawn.

## 2 Breast Image Segmentation Methods

In order to perform an automatic segmentation of the ROI in a thermal breast image, a technique that combines different methods over distinct stages is proposed. The technique consists of four stages: background segmentation, detection of bottom boundaries, detection of upper boundaries and segmentation of each breast, Fig. 1 shows the complete process and the result of every stage. In following subsections all the details of each stage are described.



**Fig. 1.** a) Input image, b) Background Segmentation, c) Detection of upper and bottom boundaries, d) Segmentation of each breast.

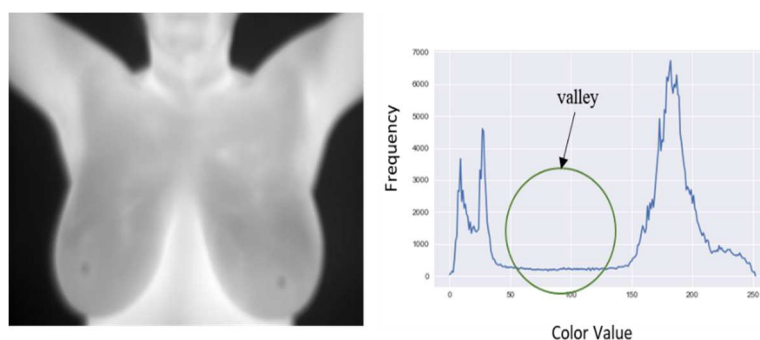
### 2.1 Database Description

The DMR (Database for Mastology Research) Database [14] is a public available breast thermogram database. The database contains breast thermograms of 287 sub-

jects out of which, the thermograms of 47 subjects are labeled as ‘Sick’ and remaining thermograms are labeled as ‘Healthy’. For acquisition of the thermograms, a FLIR SC-620 Thermal Camera with a spatial resolution of 640 x 480 pixels was used. All the images are in RGB format but the information on each channel is the same, they are in grayscale format.

## 2.2 Background Segmentation

With the aim to segment the body from the background, it is implemented a segmentation based on color intensities. Fig. 2 shows in the histogram, the contrast in a thermal image between the body and the background, clearly it can be noticed two regions separated by a valley. The region on the left represents the darker color values (background) and the region of the right represents the brighter color values (body) in the image. In order to separate both regions we found a threshold value between them. Each region can be represented as a class of color, and a common technique for automatically find a threshold value between two color intensity classes is the Otsu’s method [15], so the first step is apply this method to the input image.



**Fig. 2.** Grayscale image histogram showing two regions and a valley between them.

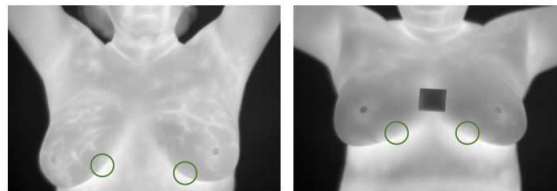
With the threshold value found by Otsu's method, all the values which are under the threshold are considered as part of the background. With the objective of detect easily this region, a control color value is considered and applied to the image. Equation 1 shows the applied rule, where  $x$  is the input color value,  $cc$  is the control color value and  $th$  is the threshold value found:

$$f_{th}(x) = \begin{cases} cc, & x \leq th \\ x, & x > th \end{cases} \quad (1)$$

In Fig. 1b the result of applying the background separation is shown. In the segmentation process in some cases, some parts of the body such as nipples are modified due the threshold value, a solution to this affected regions is presented in section 4.

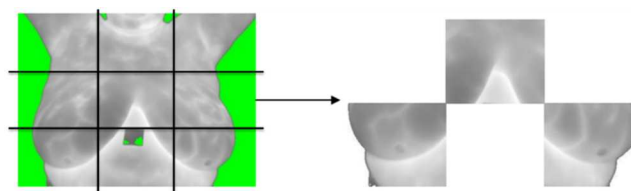
### 2.3 Detection of Bottom Boundaries of the Breasts

The next stage is one of the most difficult in the whole process, the detection of bottom boundaries. In this work we propose an approach based on local patterns such as variations in color intensities. The first step of this stage is automatically find a threshold value that it can separate the regions related with the highest temperatures in the body from the rest. In thermal images the highest temperatures are represented with brighter values and the lower temperatures with darker values. This is relevant for the database images because the regions with the highest temperatures are present in armpit, neck, and under the breasts; the latter region is what we want to identify. Fig. 3 shows bottom boundaries of the breasts where the temperatures are higher in comparison with others regions in the body, these temperatures are represented with brighter values.



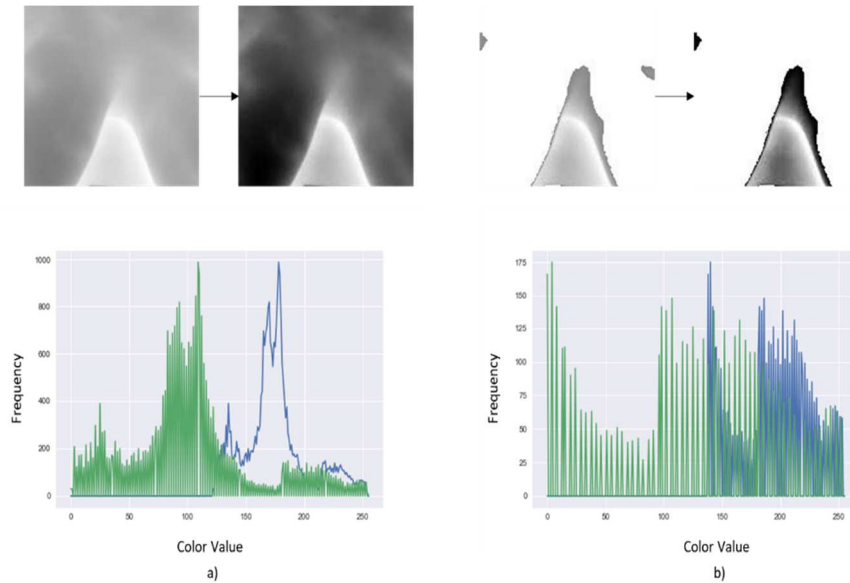
**Fig. 3.** Higher temperatures in bottom boundaries of the breasts.

In order to face this problem a local analysis is carried out. The image is divided in three sub regions from up to bottom, and in other three sub regions from left to the right. After this process the image has nine sub regions. The principal sub regions to analyze are the middle column in the second row, and the left and right sub region in the last row, because these areas contain the information related with the bottom boundaries of the breasts in most of the images, only in a few images this may not be true. The division of the image is showed in the Fig. 4. After identify this sub regions the technique discard the rest of the sub regions to the following operations.



**Fig. 4.** Image divide into nine regions and the selected images.

In every image of the chosen sub regions an accumulative contrast enhancement [16] is performed, so the brighter color values are separated from the dark color values, this is important in order to discard the lower temperatures values of the breasts because these values are considered as noise in this stage and they can affect the posterior analysis. Fig. 5a shows the result and the histogram of the original image and after the contrast enhancement is applied in one of the selected sub regions.

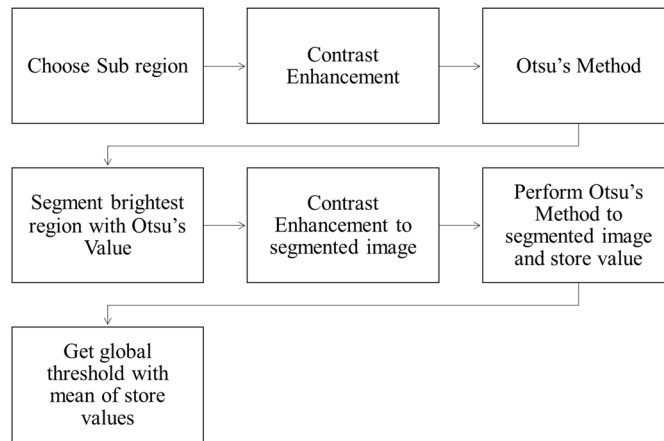


**Fig. 5.** a) Original image and contrast enhancement image and its histograms (blue for the original and green for the altered image), b) Image segmented and contrast enhancement and its histograms (blue for the original and green for the altered image).

With the aim to remove the darkest color values, Otsu's method is applied. Any color value that is over the threshold value found is segmented. At this moment it has been removed many dark values as is showed in the left image in Fig. 5b, and also it can be notice that the region under the breast it remains. In the segmented region a second contrast enhancement is applied to enlarge the difference between the bright and dark color values. The Fig. 5b shows the result of second contrast enhancement, it can be noticed how it was enhanced the region of the bottom boundaries of the breasts in the image. Now the boundaries are better than in the input image.

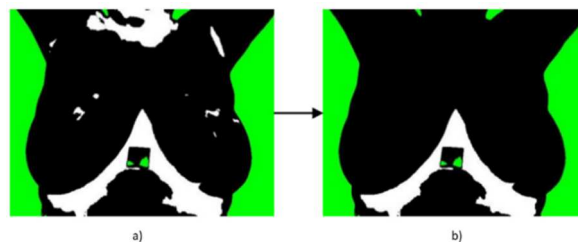
Otsu's method is performed one last time to obtain a threshold value who it can segment the brightest color values in the local sub region, this returned value is stored in a list. After this procedure is applied for every one of the three sub regions, three local threshold values are found, with these values the mean is calculated, this is considered as the global threshold value, lastly with this value a binarization is applied to the input image of this stage. Fig 6 shows a diagram of the process to follow in the chosen sub regions to automatically find the threshold value who segments the highest temperatures regions from the rest.

Fig. 7a shows in white color the regions of the highest temperatures present in the body after the binarization. As it was expected, these regions are in the neck, armpits, under the breasts and in some small regions around the body. Also the biggest region is under the breasts, so the procedure focus in locate it and discard the rest of them. The regions of the upper half body are discarded because they are not relevant to this stage, so they are set it to a black color.



**Fig. 6.** Diagram of the process to automatically find the threshold value who segments the highest temperatures, the first six steps are performed for every sub region, the last one is performed a single time.

Then we form clusters, regions that are composed by white points that are neighbors between them, for every point is stored its coordinates. A cluster can be view as a list of points. The clusters are stored in another list, and sorted from the region with more elements to the region with fewer elements. The technique only analyses the two biggest regions, in which it is checked a condition between them, if the proportion of the second region with more elements is at least 34% (this value keeps the most relevant data and we found it through empirical experiments over all the images), then this region is considered part of the boundary, but if this condition is not reached, only the region with more elements is considered, all the remaining regions are discarded and set it to a black color. The Fig. 7b illustrates the final result of this operation.



**Fig. 7.** a) Image binarized with the threshold found, b) Final result after removed the undesired regions.

Finally a simple process of thinning is applied. In a loop over the image from the left most column to the right most column, and from the first row to the last, when a white color value is detected, a control flag is turn on, while this flag is on any other white color value detected in the same column is set it to a black color value, when

the loop pass to another column this flag is turn off until is detected another white color value. The final result are two curves which represent the bottom boundaries of each breast.

Then a spline cubic interpolation by the Lagrange's method is performed for every breast with the aim to fit the detected curves, the method return a polynomial that it can be used to extrapolate the curve to any other point. Finally with the polynomials, the intersection point between the curves can be calculated equalizing them to zero and solving the equation. The final result is shown in Fig. 8.

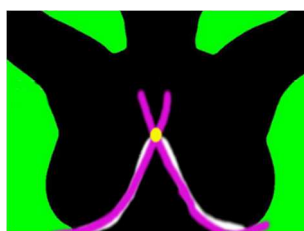


Fig. 8. Thinned line in white, curve fitting in purple and intersection point in yellow.

## 2.4 Detection of Upper Boundaries

The next task is to find the upper boundaries. For this step it is used the information related to each boundary side and the information of the previous stage. Along with this data some statistical operations are performed. The coordinates in the x and y axis where exists a transition from the background to the body are saved in a list, one list for each side. The lists are generated from down to up of the image, so the first points correspond to coordinates close to the breasts and the latest are near of the arms in the image. Then is calculated the mean  $\mu$  and deviation standard  $\sigma$  of the x coordinate values for each list as is showed in equation 2 and 3:

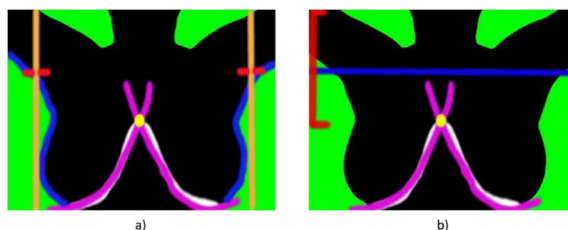
$$\mu = \frac{1}{n} \sum_{i=1}^n X_i, \quad (2)$$

$$\sigma = \sqrt{\sigma^2} \text{ and } \sigma^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2. \quad (3)$$

Where  $X_i$  is the x coordinate value and  $n$  is the total points in the list. Due to the body posture in the images, the mean is close to the armpit and arms, this happens because the majority of the x coordinate values are present in this area. The standard deviation give a plus/minus range of how much the values are spread from the mean, the technique find the first value outside this range. As it is known the order of the list (down to up of image), in a loop over all of the points in each list, it is going to be found the first point where its x coordinate value is greater than the sum of the mean plus/minus (depending of the body side) deviation standard, this point is stored. This analysis is made for each side. The points found are usually different and only one point is considered, a comparison is performed between them and the one with the highest y coordinate value is selected. Besides that, it needs to be checked if the selected point is inside the area delimited by the point of intersection between the breasts found in the



previous stage and the first row of the image, this is done with the aim to avoid bad results. Fig. 9a shows an example of the stored points of each side, the mean and standard deviation calculated and Fig. 9b shows the final result of this stage.

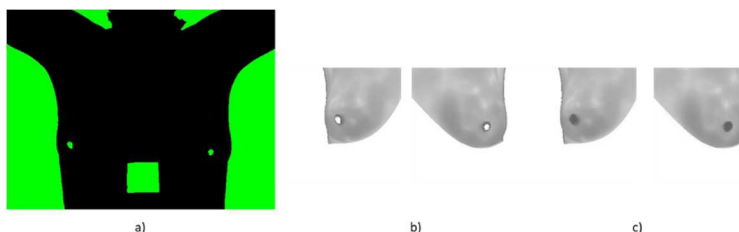


**Fig. 9.** a) Points over the blue region are stored in the described lists, the mean in the x coordinates is close the orange lines and the standard deviation is a plus/minus range represented with the red lines, b) In red is shown the check range where the upper boundary needs to be, in blue the final upper boundary detected.

## 2.5 Correction and Segmentation

Finally the segmentation of each breast is performed, to achieve this it is used the data of the boundaries and the point of intersection of the previous stages. All the points inside the upper, bottom and lateral boundaries are considered, and the point of intersection between the breasts is used as middle point, finally two images are created and the background color is removed as a final step.

The input image of this stage is the output image of the first stage, this image is very useful because the lateral boundaries are known due the control color of background and all the original values in the body are present in the rest of the image. Sometimes a few parts of the body have very dark values that are wrongly set it to the background color, so this represents a loss of information. If this case happens a correction must be applied with the image resulting of the first stage and the input image (original image). This is fixed with a procedure that visits all the neighbors in a window of 3x3 for a central point. This procedure checks if the value for the central point is the same of the most repetitive value of its neighbors, if the condition fails, the value for the central point is restored to the original value. Fig. 10 shows a corrupted image, and the result of the correction.

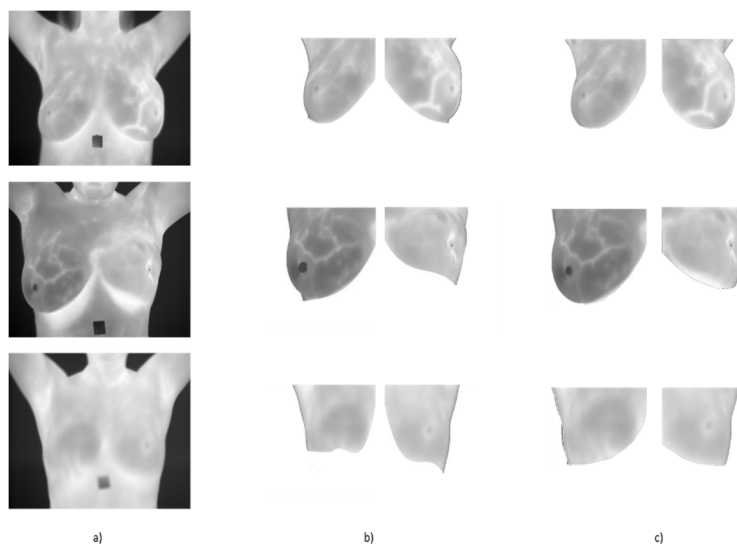


**Fig. 10.** a) Image corrupted by the procedure of the first stage, b) Segmented image with loss of information, c) Final Image with original values recovered.

### 3 Experiments and Discussion

The proposed method was tested on 207 images from the DMR database [14] in order to evaluate it. The development of the technique was realized with Python, most of the project was an original development but some packages were used, such as scipy [27], numpy [28] and scikit-image [29].

Some results are showed in Fig. 11, the image of the first row shows an example of a case with clear color transitions under the breast and in the body, the result proves that the method achieved a very good result; the image of the second row presents a case where one of the breast has been part of a medical procedure, in spite of this, the method approximate very accurately the region of both breasts; in the final row it is presented an image where the color transition in the boundaries under the breast are not clear, nevertheless the result is also pretty good. All this results showed that the proposed technique works well in many possible scenarios.



**Fig. 11.** a) Input image, b) Segmented ROI by the proposed technique, c) Segmented ROI in the Ground Truth.

After performed tests in all the images around 85% were segmented with a result from acceptable to accurate. It was defined as an acceptable result any outcome where the ROI does not suffer any loss of information, even if some extra information is present in the image, e.g. small areas under the breasts that are not part of the ROI. The acceptable images are very useful because they introduce only a small amount of noise (data not belonging to the ROI), so this images can be used in future analysis such as pattern recognition without seriously affect the results. Some examples of different results are showed in Fig. 12. A summary of each kind of image is presented in Table 1.

In order to evaluate the obtained results, the segmented images by the proposed technique and a Ground Truth (elaborated by ourselves) of manual segmented images were used. Each image was compared with its counterpart in the Ground Truth and the difference between each one was calculated as a percentage. Fig. 11b shows some examples of the Ground Truth. Finally, the average of all percentages were calculated as an accuracy measure. Comparing with the research of Marques et al. [12] and Villalobos-Montiel et al. [13] who used the same database, the outcome is competitive, the results are listed in Table 2.

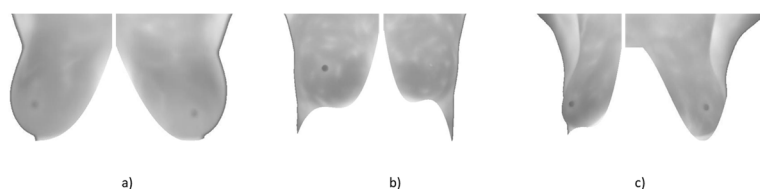
**Table 1.** Analysis of the segmentation process result.

Result	Total	Percentage
Segmentation		
Accurate	160	77.3%
Acceptable	15	7.2%
Poorly	32	15.5%

**Table 2.** Comparison in segmentation accuracy.

Author	Accuracy
Marques et al.	96.0%
Villalobos-Montiel et al.	98.7%
Proposed technique	94.0%

The main contribution of this work is it only takes into account simple operations such as contrast enhancement, local analysis and statistical operators in order to find the upper and lower boundaries. Obviously this techniques will not work with other databases because the acquisition protocol of the images might be different, and an important fact for the method, at least for the step of detecting the upper boundaries in the ROI is the applied protocol in the DMR database, but a brief analysis and few modifications are necessary to achieve the same results with a new data set.



**Fig. 12.** a) Remarkable segmented image, b) Acceptable segmented image, c) Poorly segmented image.

## 4 Conclusions

This paper presented a technique for automatic segmentation in breast thermal images. The ROI extraction in medical domains is an important step in the development of systems for medical diagnosis based on digital images, because an accurate segmentation allows a better analysis of the most relevant information in the data. It was shown through the methodology and the performed experiments that this is not an easy and trivial task.

The proposed approach is based on local analysis with the aim to avoid global noise. Intrinsic characteristics in the image are used to identify borders, such as body posture or temperatures related with color values.

The technique showed good results even in images where the borders of the ROI are unclear, in spite of this, there are some errors in images with low contrast in the region of the breasts, amorphous breasts and in images with too many regions of high temperatures around all the body. These cases are an opportunity to keep working in the technique and improve the results. As a future work, the second stage of this project will be addressed, the stage related to feature extraction from segmented images where we will propose approaches for the classification task.

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