

Detection of Breast Diseases by Sierra Lite Dithering on Mammographic Images

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Abstract:

This paper proposes an algorithm for the detection of masses and Mcs on digital mammography images by sierra lite dithering which provides a representation of the region of interest and highlights the other bodies present on the image. The results are highly accurate, allowing better detection of breast pathologies (mass and micro-calcification). A filtering step (median filter) is started first to eliminate noise, then a Sierra Lite dithering step is used to detect masses and Mcs. Then a morphological opening step is used here to eliminate the noise generated by the dithering. Finally, the Prewitt contour detection is used to highlight the masses and Mcs. The tests were conducted on the database of a Health and Internet clinic. The results obtained show the robustness of the proposed dithering method. In order to evaluate the efficiency of our pathology detector, we performed a evaluation with a rate of 98.04% for the detection of masses and 70% for the detection of Mcs. A radiologist from the health clinic evaluated the results and considered them acceptable for CAD. Moreover, we point out that it also works on all devices and is capable of real-time image processing.

Keywords: sierra lite dithering; median filter; pathology detector; morphological aperture; evaluation

Mathematics Subject Classification: 62P12

Journal of Economic Literature (JEL): Q50

1. INTRODUCTION

Breast cancer is the most common cancer among women in developed western countries and is becoming increasingly important in many developing countries (Yousef, 2005; Althuis et al., 2005). Although incidence rates are increasing, mortality rates are stable, representing an improved survival rate. This improvement can be attributed to effective early detection, primarily mammography, as well as significant improvement in treatment options (Freedman L. S. et al., 2006). Furthermore, "breast carcinoma is not a systemic disease at its origin, but a progressive disease and its development can be stopped by screening" (Tabar et al., 1999; Anderson T. et al., 2000). Early detection of breast cancer, while still small and confined to the breast, offers the best chance of effective treatment for women with the disease (Ferlay J., 2004; Parkin D. M. et al., 2005).

Breast cancer detection by mammography is performed by a human reader, usually a radiologist or oncologist. The causes of missed breast cancer at mammography can be secondary to many factors, including those related to the patient (whether inherent or acquired), the nature of the malignant mass itself. Even poor mammography techniques or human reader interpretation skills (including perception and interpretation errors) (Kamal R. M et al., 2007).

Perception error occurs when the lesion is included in the field of view and is obvious, but not recognized by the radiologist. The lesion may or may not have subtle malignancy characteristics that make it less visible. Small, unspiculate masses, areas of architectural distortion, asymmetry, small clusters of amorphous or weak micro-calcifications, all can be difficult to perceive (Kamal R. M et al., 2007). On the other hand, a misinterpretation occurs for several reasons, including lack of experience, fatigue or inattention. It may also occur if the radiologist is unable to obtain all the views necessary to assess the characteristics of a lesion, or if the lesion is slow growing and prior images are not used for comparison (Kamal R. M et al., 2007; Radhika S., 2005).

To assist human readers and minimize the effect of perception and interpretation errors, DECAs have been introduced. A Computer Aided Detection (or Computer Aided Device) (CAD) “refers to a computer algorithm that is used in combination with an imaging system to assist the human image reader in detecting or classifying a disease” (Wagner R. F. et al., 2002). CAD systems reduce human errors that lead to missing breast carcinoma, either due to poor perception or misinterpretation, which could increase the sensitivity of mammography interpretation (Muttarak M. et al., 2006). CAD, in the United States receives radiologist attention and its use has increased rapidly; however, this is not the case in many parts of the world (Rao V. M. et al., 2010) like developing countries where there is a critical lack of equipment and well-trained staff.

To give all the states of the world the chance to detect the different breast pathologies that we develop this CAD.

The rest of this manuscript is organized as follows. Section 2 is a history and brief review of the literature on the associated computer methods applied to the detection of breast diseases. Section 3 describes the Presentation of the method and protocol used and the database used in this article. The results, discussions and evaluation are described in Section 4. The following section concludes the article and discusses current and future work to complement this article.

2. STATE OF THE ART

In Diagnostic Aid Systems (CAD), the segmentation of breast masses and micro-calcifications are an important and delicate task as subsequent processing of description, classification and registration is strictly related to the outcome of the segmentation. Consequently, a good detection of the lesion

contour produces a description that is true to its characteristics. As a result, a classification can be ensured that minimizes the rate of false positives and maximizes the rate of true negatives.

However, mass detection has been shown to be more difficult than Mcs detection (Malagelada A. O., 2007). It is difficult to distinguish between masses and normal regions due to their low contrast and ambiguous edges partially masked by the tissue.

Thresholding methods have greatly served the segmentation of breast masses. (Kom et al., 2007) detected suspicious masses from adaptive thresholding mammography images. The proposed algorithm was tested on a database of 61 mammography images with masses previously marked by experienced radiologists. The results show that the proposed method has a sensitivity of 95.91% for mass detection. (Kurt B et al., 2014) propose a new segmentation algorithm to identify candidate mass regions in mammograms. The proposed system consists of three parts: breast region and pectoral muscle segmentation, image enhancement and identification of suspicious mass regions. In this study, we focused on identifying suspicious mass regions using a combination of the Havrda and Charvat entropy method and the Otsu thresholding method. A Mammographic Image Analysis Society (MAM) open access database of 59 masses was used for the study. The proposed system achieved a sensitivity rate of 93% for the identification of suspicious mass regions in 56 abnormal and 40 normal images. While, (Leger B.Y. et al, 2021) proposes a new algorithm for mass and micro-calcification detection using manual thresholding and prewitt detector. A local and internet database, which contains 40 images, was used for the study. The proposed system achieved a sensitivity rate of 98.04% for breast pathology detection. A radiologist from the health clinic evaluated the results and considered them acceptable for CAD.

Similarly (Leger B.Y. et al., 2021) proposes an algorithm for identifying regions of interest by inverse contrast enhancement that provides a representation of the different contours (mass, pectoral muscle, outer breast contour, and Mcs). The second contribution is the detection of masses and micro-calcifications by manual thresholding and prewitt detector. A local and internet database, which contains 40 images, was used for the study. The proposed system obtained a qualitative evaluation with a rate of 99% for the identification of the different contours and 98% for the detection of breast pathologies. A radiologist from the health clinic evaluated the results and considered them acceptable for CAD.

In this same context, (Alain Tiedeu et al., 2012) developed a method to detect micro-calcification based on texture. The input image is smoothed and subtracted from the contrast enhanced image of the input image. The detection method showed 85.65% success rate with a 2.50 FP image. The classifier showed a better classification under ROC with 96.8%. Some authors use morphological methods to detect different breast pathologies.

Thus, (Zhang X.et al., 2013) uses a combined morphological operation transformed into wavelets to detect Mcs in mammograms. Micro-calcifications are first improved by using the morphological

treatment of multi-structure elements. Next, candidates (area) for micro-calcifications are refined by a multi-level wavelet reconstruction approach. Finally, the MCs are detected according to their distribution function. Experiments are performed on 138 clinical mammograms. The proposed method detected 92.9% of true Mcs cluster per image and 0.08% of false MCs cluster per image. Another author uses variational methods for segmentation and detection of breast pathologies. Thus, (Peyman Rahmati et al., 2012) presented a new maximum probability active contour model using level sets (MLACMLS). The segmentation contour is estimated using the gamma distribution. The proposed algorithm is compared to the adaptive level-based segmentation method (ALSSM) and to speculative level-based segmentation (SSLS). The accuracy of MLACMLS is 86.85%, while ALSSM is 74.32% and SSLS 57.11%. The results are compared qualitatively to the active contour and showed better performance.

Similarly, (Rahimeh Rouhi et al., 2012) developed two methods to segment the masses of the input image. In the first method, automated region's growth is used to segment the threshold in which the threshold is obtained by the artificial neural network (ANN). In the second method, the cellular neural network (CNN) is used for segmentation in which the parameters are obtained by a genetic algorithm (GA). The proposed method is compared to random forest classifiers, naive Bayes, SVM and KNN. The developed method obtained a sensitivity of 96.87%, a specificity of 95.94% and an accuracy of 96.47%.

In the same context, (Abdul Malek et al., 2010) combined the growth of seed-based regions and segmentation of contours in a sequential order. The first process of growth in the region is to identify an initial starting point. Most regional growth methods manually identify the germ point that involves human interaction, and is thus considered the initial starting point (germ) for our region growth algorithm. The contour segmentation method is implemented to improve segmentation results. The method is tested on 50 mammography images confirmed by a radiologist as micro-calcifications. Experimental results show that the algorithm successfully segments, micro-calcifications with an accuracy of 0.94.

Several research studies have been carried out on the segmentation of mammographic images which differ in the various approaches used and their tendency to act in an automatic or semi-automatic manner. However, it will be difficult to classify the methods proposed in the literature according to the approaches used, previously seen as the authors propose segmentation in several steps to achieve the desired objective.

3. Materials and methods

Following is the flowchart of the proposed approach

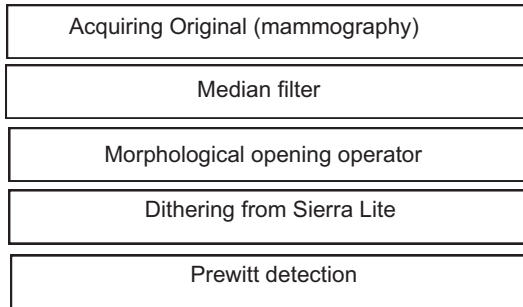


Figure 1. The main steps of the breast lesion detection algorithm

Step 1: Acquisition of digital mammograms

Approximately 40 pairs of conventional lateral and cranio-causal mammograms were selected as part of the screening program for the detection of breast pathologies currently underway in a health clinic and on images taken on the Internet (20 each). Each pair of mammograms being successive to contain a single malignant mass that the radiologist recommends to biopsy in the left or right mammogram. The mammograms were digitized with a commercially available Senographe T800 laser scanner. After scanning, each digital mammogram was subsampled to obtain an image of 600 * 887 pixels. These reduced versions were used in the initial stages of the method for calculation purposes.

No field truths were available for these data obtained from the internet (no radiologist or histology report). We therefore conducted a case review with several medical imaging experts.

Step 2: median filters

The images in our database are likely to contain noise as they are obtained from several sources. For this reason we perform a pre-processing (filtering) to reduce noise and to preserve certain details. Moreover, we use the median filter because it eliminates noise while preserving the contours of the image, while the Frost Filter has the advantage of smoothing the homogeneous areas, and preserving the contour and line transitions. Whereas, Lee first proposed a filter in the case of additive noise. Finally, the Kuan filter first transforms the multiplicative noise model into a signal-dependent additive model.

The median filter (Zhang X.et al., 2013) is a non-linear digital filter, often used to combine both efficient suppression of impulse noise and preservation of sufficiently important details in the image. It works by replacing the value of one pixel with the median value of all pixels in its neighborhood. This

filter also removes isolated pixels. Thus we can observe the results of the filtering in figures 2 b), 3 b), 4 c) and 5 b).

Step 3: Dithering from Sierra Lite

The Sierra Lite (Raja Bala and Victor Klassen, 2002; Floyd R. and Steinberg, 1976) dithering algorithm is a kind of dithering algorithm based on error diffusion, simple and quick to use form. It quantifies the current image pixel at two gray levels of 0 or 255 depending on the threshold, then spreads the quantification error residuals of a single pixel over a plurality of adjacent unprocessed pixels according to a certain ratio, thus achieving the color reduction of the image. The principle of error propagation can be expressed as follows:

$$I'(i,j) = I(i,j) + \sum_{k,l \in S} w(k,l) e(i-k, j-l)$$

Where $I(i,j)$ am the original image, and $I'(i,j)$ am the gray value of the original image after addition of the quantification error of the diffusion of surrounding pixels in $I(i,j)$. The quantification error $e(i,j)$ is distributed to neighbouring pixels by a two-dimensional weighting matrix $w(k,l)$, also known as the scattering kernel. The diffusion core of the Sierra Lite dithering algorithm is:

$$W(k,l) = \frac{1}{4} \begin{bmatrix} - & x & 2 \\ 1 & 1 & 0 \end{bmatrix}$$

Here, the values of 2, 1, 1, 0 in the matrix represent the error diffusion rate, x represents the pixel being processed, and $-$ represents the pixel that has been processed. The algorithm quantifies a single pixel each time and performs the whole image quantification process by scanning the image line by line.

The results of Sierra Lite dithering are shown in Figures 2 c), 3 c), 4 c) and 5 c).

Step 4: morphological opening operator

Parasitic details generated by the thresholding step are eliminated using a morphological opening operator (Gonzalez R. and Woods R., 1992; Byng et al., 1997) with a circular structuring element of size 3. We use a small size as a structuring element because if it is very large it will make the ROI disappear. The effects of the morphological aperture are:

- The disappearance of small particles (whose size is smaller than the size of the structuring element)
- To separate coarse particles where they are finer.

Thus we can observe the results of the morphological opening operator in figures 2 d), 3 d), 4 d) and 5 d).

Step 5: Prewitt detection

After the morphological opening operator, we finally perform the edge detection to highlight the region of interest.

Thus, the Sobel and Prewitt detectors produce thicker and therefore less localized contours than Roberts' operator, but are more resistant to noise.

These two operators give identical results in terms of thickness and contour localization, but differ slightly in terms of noise resistance (different low-pass filtering).

The Prewitt operator (Gonzalez R. and Woods R., 1992) is used, especially in edge detection.

The operator calculates the gradient of the image intensity at each point, giving the direction of the largest possible increase of light to dark and the rate of change in this direction. The result thus shows how "abruptly" or "smoothly" the image changes at that moment - there, and thus the probability is that part of the image represents an edge, and how that edge is likely to be oriented. Thus we can see the results of Prewitt's Detection in figures 2 e), 3 e), 4 e) and 5 e).

4. Results, Discussion and Evaluation

In the example shown in the figures below, we applied the process described in Figure 1. The mammography techniques were applied to the images in our database on the parts of the light region considered interesting. It should be noted that radiologists at the health centre diagnosed three images from Figure 2a), Figure 3a), and Figure 5a) of probable breast cancers. In particular, he recommends in Figure 2a) a biopsy to confirm the diagnosis and in Figure 3a) a blood test. The radiologist diagnosed benign calcification figure 4 and breast cyst figure 5. The results presented here (some) were marked by a radiologist.

The results of the detection procedure were analyzed according to the protocol described in Section 3. A total of 40 images were analyzed; four examples of results are illustrated in Figures 2 to 5. It should be noted, from the example in Figure 2, that the process works well and produces satisfactory results. It even makes it possible to identify and detect masses, and Mcs. Indeed, this detection and identification is only possible thanks to the dithering of Sierra Lite. It should be noted that for the Mcs when they are small, we cannot detect the Mcs well because they are confused with the rest of the image, which does not allow a good detection of the Mcs in these cases.

Figure 2a) 3a) 4a) 5a) presents a mammographic image that is to be used for various transformations as shown in Figure 1.

The median filter is used here to reduce noise while maintaining the contours of the image, it also allows to remove the isolated pixels. It is used here with a filter width =3 and the percentage of the pixel retained is equal to 50%. We can observe the results of the median filter on figures 2b), 3b), 4b) and 5b).

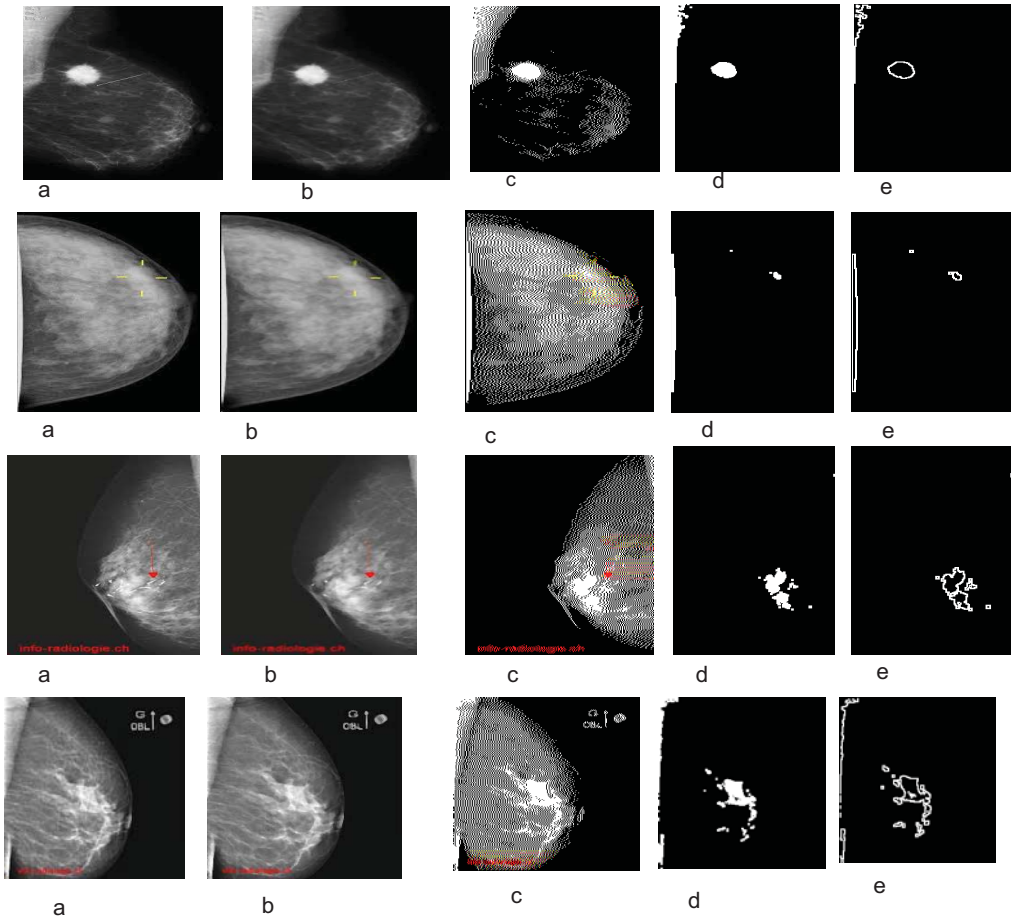


Figure 2-5. Results of the detection of masses and Mcs. (a) Original image (b) Image after median filter, (c) Image after dithering of sierra Lite (d) Image after application of the morphological aperture

Figures 2c), 3c), 4c) and 5c) present the Sierra Lite Dithering operation of adding small amounts of noise to a signal to reduce the noise of low-level distortion in an image. A small amount of random noise is added to the analog signal before the sampling step, reducing the effect of quantification errors. By adding a special type of noise at extremely low levels, quantification errors are minimized. The added noise can be perceived as a very low noise in the image. However, it is barely visible and preferable to the distortion that occurs otherwise. Noise Formatting options allow us to filter this noise over an area of frequency that is less visible to the human eye. We use dithering with two colors per channel as parameters and the channel used is RGB.

Figures 2d), 3d), 4d) and 5d) present the applied morphological aperture application, to previous images, considerably eliminates the parasitic details generated by the dithering step with a size or disk of 3 and dark outer edge.

Finally the Prewitt operator is used for edge and contour detection. The results of the Prewitt detector can be seen in Figures 2(e), 3(e), 4(e) and 5(e). It highlights masses and micro-calcifications.

Evaluation and comparison of results with literature

The detection of masses and Mcs of our process defined in figure 1 on a set of 40 images (thus 20 images of a health clinic, and 20 images of the internet). Depending on the result obtained, the algorithm succeeds in identifying exactly the focal points of the Mcs, masses on the mammography images.

To demonstrate the robustness of the algorithm, it was tested on mammograms with different breast tissue densities. Overall, for the mammograms evaluated, the average quality measure values for mass detections were 0.985 and the average quality measure value for Mcs detection was 0.7. This means that the algorithm seems extremely robust when it comes to density types, especially for masses.

Table 1: Comparison of the results obtained by our approach with those of the literature

Name author	Method used	Number of images	Accuracy, sensitivity etc...	Results
Kom et al.	thresholding	61 clinical images	95.91%(sensitivity)	Mass detection
Abdul Malek et al.	Region growth+ contour segmentation	50 clinical images	94%(accuracy)	Mcs detection
Zhang et al.	Morphological and wavelet operation	138 clinical images	92.9% true Mcs cluster per image and 0.08% false	Mcs cluster per image Mcs cluster detection
Leger B.Y.	manual thresholding and prewitt detector	40 clinical images	sensitivity rate of 98.04%	Mass, Mcs detection
Our approach	Dithering of sierra Lite	80 clinical images + internet	98.5% mass detection 70% Mcs detection	Detection of breast pathologies (masses, Mcs)

The table summarizes some recent works of segmentation (of masses, Mcs) validated on digital mammography images. From this comparison, we can see once again that our method works well and gives very satisfactory results for the detection of masses and Mcs.

5. Conclusion

The obtained results reveal that the proposed Computer-Aided-Diagnosis (CAD) tool is robust for the automatic detection of breast cancer.

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