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WINDOW SIZE EFFECTS USING CLAHE FOR CONTRAST ENHANCEMENT IN MAMMOGRAPHIC DENSE BREAST IMAGES

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Abstract: Breast cancer is the second most common type of cancer among Brazilian women, globally recognized as a major public health problem. Dense breasts increase the risk of developing breast cancer, mainly due to the difficulty of the lesion visualization, hampering the probability of early detection. In order to enhance the overall quality of mammographic images, digital image processing techniques could improve the visualization of lesions, providing an increase in contrast among breast structures. The goal of this paper is to evaluate the use of the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique for contrast enhancement in mammographic dense breast images. By computing the signal to noise ratio (SNR) and variance, comparing the original images to the processed ones using CLAHE. In this paper, 28 dense breast images were used and separated in mediolateral oblique (MLO) and craniocaudal (CC) views. All the images were processed after the background removal, using CLAHE with seven different window sizes. The results showed that small window sizes decrease the SNR. However, by decreasing window size, an increase in variance was observed, therefore increasing contrast. This increase in contrast was visually observed, on which processed images using small window size performed better enhancement for breast structures, thus resulting in greater contrast. According to these results, we concluded that the CLAHE technique performed better using small window size. In future works, we should apply this algorithm in a greater dense breast image database, as well as preprocessing the images by digital filters for reducing noise.

Keywords: CLAHE, **c**ontrast enhancement, dense breasts, mammographic images, SNR.

Introduction

Cancer is a major public health problem in both developed and developing countries [1]. Breast cancer is the second most common type of cancer among women in Brazil after non-melanoma skin cancer [2]. Some researches directly relates breast density to the risk of developing breast cancer [3-7] i.e., greater predominance of fibroglandular tissue in breast (dense breast) increases the risk of breast cancer up to 4 to 6 times when compared to women with fatty breasts [8].

Mammography is the main medical imaging technique for screening breast cancer. This technique has verified effectiveness for early diagnosis of breast cancer, reducing the mortality rate and increasing the probability of cure [2].

However, the image quality is the decisive factor for the assessment by an experienced radiologist. Hence, some researches [9-12] propose digital image processing techniques to enhance the contrast in mammographic images, improving the visualization and characterization of breast lesions. Moreover, dense breasts have a predominance of fibroglandular tissue, decreasing the contrast between a lesion and the mammary tissues. Thereby a proper technique for enhancing the overall quality of dense breast images is desired and an important research area.

In this paper, the goal is using and evaluating an adaptive contrast enhancement technique based on histogram equalization for mammographic dense breast images. By calculating the signal to noise ratio (SNR) and variance (VAR), the idea is to compare the original image to the processed image using the proposed technique.

Materials and methods

The images used in this work are available in the INbreast database, provided by São João Hospital Center in Porto, Portugal [13]. The entire database was acquired using the MammoNovation Siemens Full-Field Digital Mammography, and the images were saved in Digital Imaging and Communications in Medicine (DICOM) format, fully anonymized and previously assessed by expert staff.

Out of a total of 410 images available in the database, we only used 28 images that were assessed as dense breast, i.e., breasts classified as “d” according to the Breast Imaging Reporting and Data System (BI-RADS®). The size of the images varies between 3328 x 4084 or 2560 x 3328 pixels, depending on the compression applied in the breast.

Since mediolateral oblique (MLO) views contain a section of the pectoral muscle, that may affect the computed values of signal to noise ratio (SNR) and variance (VAR), we separated the MLO from the craniocaudal (CC) views for a better comparison, resulting in 14 images of each incidence (14 MLO images and 14 CC images).

The images were pre-processed by removing the background (zero values). For the contrast enhancement,

we used the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm proposed in [14], and summarized in [15]. This technique operates in predefined windows chosen by the user, on which the contrast is enhanced, changing the pixel values of each window (region), by means of a clip limit.

The clip limit is a user defined threshold that truncates the image histogram. The exceeding values are then redistributed to other intensities by the CLAHE algorithm. In other words, the intensity values above the threshold is equalized before computing the cumulative density function (CDF) that results in the final image. Figure 1 briefly shows the original histogram transformation into an equalized histogram by means of a clip limit.

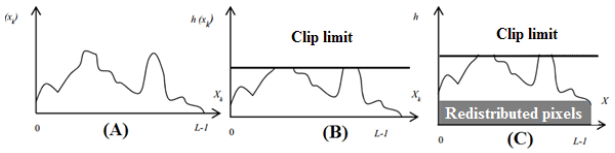

Figure 1: (A) Original histogram; (B) Histogram clip limit; (C) After the clip limit, the pixels above the threshold are redistributed, creating a new histogram [16].

In this paper, we tested windows of size 500 x 500, 250 x 250, 100 x 100, 18 x 18, 15 x 15, 9 x 9, and 3x3 pixels, using a clip limit of 0.01, the default value. This approach should allow us to assess the behavior of window size for each image.

After processing all images using the different window sizes, we calculated the SNR (Equation 1) for all the output images, comparing with the SNR calculated in the original images. Subsequently, we calculated the average and standard deviation for both 14 MLO images and 14 CC images, separately. The SNR used in this work is calculated according to Equation 1 [17],

$$SNR\ (dB) = 20 \log_{10}\left(\frac{I_{max} - I_{min}}{\sigma_{Image}}\right) \qquad (1)$$

where I_{max} and I_{min} are respectively the maximum and minimum values of pixel intensity of the image, and σ is the image standard deviation.

Besides SNR, we also calculated the variance (VAR) for all output images, since this measure it is related to contrast measurement. At last, we visually assessed images containing nodules, comparing the algorithm tested using different window sizes.

Results

Tables 1 and 2 shows the average and standard deviation values of SNR and variance for MLO and CC views, respectively. It is possible to compare the values obtained without the CLAHE technique (original images) and after the processing with different windows size.

Table 1: SNR and variance (average and standard deviation) of the original images and the processed images in mediolateral oblique incidence.

Incidence	**Mediolateral oblique (MLO)**	
Images	**SNR ($X \pm \sigma$)**	**VAR x10^5 ($X \pm \sigma$)**
Original	18.82 ± 1.77	0.57 ± 2.1
500 x 500	20.09 ± 1.21	0.47 ± 0.66
250 x 250	19.58 ± 1.39	0.56 ± 0.66
100 x 100	19.22 ± 1.42	0.48 ± 0.5
18 x 18	16.89 ± 0.72	0.89 ± 0.15
15 x 15	16.52 ± 0.66	0.98 ± 0.17
9 x 9	15.41 ± 0.41	1.34 ± 0.23
3 x 3	12.96 ± 0.7	2.39 ± 0.94

Table 2: SNR and variance (average and standard deviation) of the original images and the processed images in craniocaudal incidence.

Incidence	**Craniocaudal (CC)**	
Images	**SNR ($X \pm \sigma$)**	**VAR x10^5 ($X \pm \sigma$)**
Original	18.87 ± 2.07	0.59 ± 2.23
500 x 500	20.07 ± 0.66	0.48 ± 0.78
250 x 250	19.53 ± 0.7	0.61 ± 0.85
100 x 100	19.12 ± 1.26	0.65 ± 0.87
18 x 18	16.44 ± 0.4	0.93 ± 0.24
15 x 15	16.20 ± 0.62	1.09 ± 0.26
9 x 9	14.83 ± 0.63	1.45 ± 0.4
3 x 3	12.65 ± 0.77	2.4 ± 1.04

Tables 1 and 2 show that the greatest values of SNR for window size of 500 x 500, resulting in 20.09 and 20.07 dB for MLO and CC, respectively. In addition, the 500 x 500 window resulted in the smallest values of variance, 0.57x10^5 (MLO) and 0.48x10^5 (CC), even smaller than the results for the original images, without using the CLAHE technique.

Furthermore, Tables 1 and 2 show the smallest values of SNR for the window size of 3x3, which resulted in 12.96 and 12.65 dB for MLO and CC, respectively. However, this same window resulted in the greatest variance values, 2.39x10^5 and 2.4x10^5 for MLO and CC views, respectively.

In addition to the SNR and variance determination, we performed a visual analysis of the dense breast images processed by the proposed CLAHE technique. Figure 2 shows one example of mediolateral oblique incidence image that was diagnosed with a nodule. In this Figure 2 is depicted the original image (without CLAHE processing – Fig. 2A), as well as the resulting images after the seven windows tested.

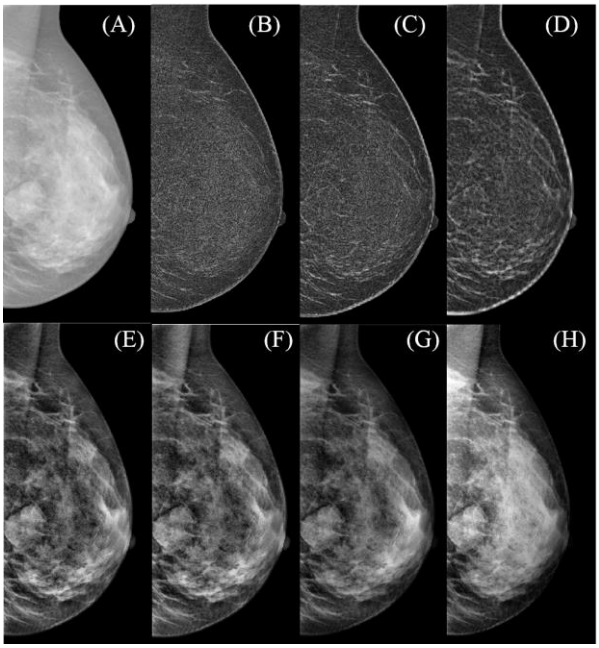

Figure 2: (A) Original image; Resulting images after CLAHE processing with windows of size (B) 500 x 500; (C) 250 x 250; (D) 100 x 100; (E) 18 x 18; (F) 15 x 15; (G) 9 x 9; (H) 3 x 3.

Discussion

The results in Tables 1 and 2 show that as the window size was reduced, lower SNR values were calculated for both views. This is directly related to the window size, since greater windows equalize greater regions, reducing the standard deviation and resulting in greater SNR, as shown in Equation 1.

On the other hand, the results showed a greater variance when the window size was reduced, suggesting a greater contrast for these images. This is illustrated in Figure 2, on which processed images using window sizes equal or smaller than 18 x 18 pixels resulted in better enhancement and structure delimitation. This pattern was not observed for images processed using greater window size (Figure 2B, 2C and 2D) and, moreover, we noticed an overall quality loss, including the reduction of pectoral muscle delimitation.

The CLAHE technique produced similar resultant images when processing using the same window size, as shown in Tables 1 and 2 by the decrease in standard deviation when comparing to the original images in both views. Such results were expected, since the intensity redistribution performed by the algorithm broadens the range of pixel values, bringing closer the similarity among images. It is worth to notice that the background removal was of utmost importance since the absolute black pixels were not taken into account when the pixels intensity values were redistributed, thus not affecting the image quality.

From the results, we also noticed that the average values of SNR and variance for both MLO and CC images were relatively similar. This indicates that the presence of the pectoral muscle in the MLO images apparently did not lead to changes in the measures calculations.

Conclusion

In this work, we evaluated the contrast enhancement performance of the CLAHE technique for dense breast images. We noticed that, even though the SNR is reduced, smaller window sizes result in greater contrast (variance).

That way, we observed that for enhancing the contrast of breast structures, the algorithm should be used along with small window size, i.e., equalizing small regions to avoid detail loss. Furthermore, in the tests of this work, the MLO and CC images showed similar results of SNR and variance averages, both in the original images and the images processed with CLAHE technique with the different windows.

As future work, we shall expand the dense breast image database, besides evaluating the influence of the clip limit parameter on the overall visual quality and quantitative contrast measurements when using CLAHE.

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References

[1] DeSantis CE, Fedewa SA, Goding SA, Kramer JL, Smith RA, Jemal A. Breast cancer statistics, 2015: Convergence of incidence rates between black and white women. CA: a cancer journal for clinicians. 2016; 66(1):31-42.

[2] Instituto Nacional de Câncer (INCA). Estimativa 2016: Incidência de câncer no Brasil. In: Instituto Nacional de Câncer José de Alencar Gomes da Silva, Coordenação de Prevenção e Vigilância. Rio de Janeiro: Inca; 2016.

[3] Byng JW, Yaffe MJ, Jong RA, Shumak RS, Lockwood GA, Tritchler DL, Boyd NF. Analysis of mammographic density and breast cancer risk from digitized mammograms. Radiographics. 1998; 18(6):1587-1598.

[4] McCormack VA, Silva IS. Breast density and parenchymal patterns as markers of breast cancer risk: a meta-analysis. Cancer Epidemiology Biomarkers & Prevention. 2006; 15(6): 1159-1169.

[5] Vachon CM, Van Gils CH, Sellers TA, Ghosh K, Pruthi S, Brandt KR, Pankratz VS. Mammographic density, breast cancer risk and risk prediction. Breast Cancer Research. 2007; 9(6):217.

[6] Schreer I. Dense breast tissue as an important risk factor for breast cancer and implications for early detection. Breast Care. 2009; 4(2):89.

[7] Pinsky RW, Helvie MA. Mammographic breast density: effect on imaging and breast cancer risk.

Journal of the National Comprehensive Cancer Network. 2010; 8(10):1157-1165.

[8] Boyd NF, Guo H, Martin LJ, Sun L, Stone J, Fishell E, Yaffe MJ. Mammographic density and the risk and detection of breast cancer. New England Journal of Medicine. 2007; 356(3):227-236.

[9] Tang J, Liu X, Sun Q. A direct image contrast enhancement algorithm in the wavelet domain for screening mammograms. IEEE Journal of Selected Topics in Signal Processing. 2009; 3(1):74-80.

[10] Bhateja V, Misra M, Urooj S. Human visual system based unsharp masking for enhancement of mammographic images. Journal of Computational Science. 2016.

[11] Lu L, Zhou Y, Panetta K, Agaian S. Comparative study of histogram equalization algorithms for image enhancement. In: SPIE Defense, Security, and Sensing; 2010 April 05; Orlando, United States. 2010. p. 770811-770811.

[12] Zhou Y, Panetta K, Agaian, S. Human visual system based mammogram enhancement and analysis. In: Image Processing Theory Tools and Applications (IPTA). 2nd International Conference on IEEE; 2010 July 7-10; Paris, France. 2010. p. 229-234.

[13] Moreira IC, Amaral I, Domingues I, Cardoso A, Cardoso MJ, Cardoso JS. INbreast: toward a full-field digital mammographic database. Academic radiology. 2012; 19(2): 236-248.

[14] Pizer SM, Amburn EP, Austin JD, Cromartie R, Geselowitz A, Greer T, Zuiderveld K. Adaptive histogram equalization and its variations. Computer vision, graphics, and image processing. 1987; 39(3):355-368.

[15] Zuiderveld, K. Contrast limited adaptive histogram equalization. Chapter VIII.5, Graphics Gems IV. P.S. Heckbert (Eds.), Cambridge, MA, Academic Press; 1994. pp. 474-485.

[16] Jenifer S, Parasuraman S, Kadirvelu A. Contrast enhancement and brightness preserving of digital mammograms using fuzzy clipped contrast-limited adaptive histogram equalization algorithm. Applied Soft Computing. 2016; 42:167-177.

[17] Moore BCJ. Hearing. 1st ed. Academic Press; 1995.