Segmentation of Breast Masses in Local Dense Background using Adaptive Clip Limit-CLAHE

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***Abstract*—Mass segmentation in mammograms is a challenging task if the mass is located in a local dense background. It can be due to the similarity of intensities between the overlapped normal dense breast tissue and mass. In this paper, a self-adjusted mammogram contrast enhancement solution called Adaptive Clip Limit CLAHE (ACL-CLAHE) is developed, aiming to improve mass segmentation in dense regions of mammograms. An optimization algorithm based on entropy is used to optimize the clip limit and window size of standard CLAHE. The proposed method is tested on 89 mammogram images with 41 masses localized in dense background and 48 masses in non-dense background. The results are compared with other standard enhancement techniques such as Adjustable Histogram Equalization, Unsharp Masking, Neutrosophy based enhancement, standard CLAHE and an Adaptive Clip Limit CLAHE based on standard deviation. The experimental results show that our method significantly improves the mass segmentation in local dense background without compromising the performance in local non-dense background.**

I. Introduction

Breast cancer is considered as a major health problem and one of the leading causes of death in women. According to the Australian Cancer Society, breast cancer is the most common cancer in women in Australia and the second most common cancer to cause death in women, after lung cancer [1]. Mammography, an x-ray imaging technique, is the best available screening tool for detecting breast cancer [2], [3]. It has shown to reduce the mortality from breast cancer by 30-40%. However mammographic sensitivity declines significantly with an increase in overall breast density [4], [5]. Computer-aided Detection (CAD) systems have been developed to help radiologists in detection of breast abnormalities on mammograms. Although it has increased early detection of breast cancer significantly [6], [7], delineation of masses located in a dense background is not an easy task [8], [9], [10], [11]. A mass is generally represented by hyperdense structure. Hence, it is difficult to differentiate between the normal dense tissue and cancerous tissue when the mass is surrounded by glandular tissues because of the similarity of intensities [12].

Some studies show that image enhancement can increase the contrast between malignant and normal tissues in dense breast and improve the mass detection [13], [14], [15]. Jo et al. [13] applied Adaptive Histogram Equalization (AHE) to increase the detection rate of cancer in dense breast. Pandey et al. [14] used Adaptive Voltera Filter to improve the contrast of mammographic masses from the surrounding tissues. Bovis and Singh [15] proposed a set of metrics (Distribution Separation Measure, Target-to-Background Contrast Enhancement Measurement Based on Entropy and Combined Enhancement Measure) to measure the quality of the image enhancement of mammographic images in a CAD for finding masses using machine learning techniques. Based on that, performance of different contrast enhancement techniques were evaluated. According to this study, a good enhancement method may greatly improve the segmentation accuracy of mass detection in dense breasts compared to the segmentation obtained from unenhanced original image. Their experimental results showed that image enhancement has a significant impact on image segmentation and optimizing enhancement on a per image basis gives better results compared to using the same method for all images. Choosing a single best technique for image enhancement is a difficult task and the performance of the enhancement is often evaluated based on the performance of the subsequent segmentation performance [16]. In this study, the performance of the proposed Adaptive Clip Limit-Contrast Limited Adaptive Histogram Equalization (ACL-CLAHE) enhancement based on entropy is evaluated using the subsequent segmentation performance.

II. Related Works

Pisano et al. [17] tested different image enhancement techniques: Manual Intensity Windowing, Histogram-based Intensity Windowing, Mixture-Model Intensity Windowing, Contrast-Limited Adaptive Histogram Equalization (CLAHE), unsharp masking, peripheral equalization, and Trex processing for digital mammography to check how these algorithms may affect the ability of radiologists to interpret the images. According to this study the CLAHE method improves the detection of simulated spiculations in dense mammograms. The CLAHE algorithm is extensively used by various researchers for CAD applications in medical imaging because of its efficiency and straightforward implementation [18], [19], [20], [21], [22].

Sundaram et al. [18] used CLAHE based contrast enhancement for mammograms. Rahmati et al. [19] used fuzzy CLAHE as a preprocessing filter to eliminate the noise and intensity inhomogeneities in mammograms to improve segmentation of masses. Wu et al. [21] adopted CLAHE to enhance the high frequency subbands coefficients in-order to enhance the features and image contrast. Maitra et al. [22] also used CLAHE as a preprocessing technique for digital mammograms. CLAHE can effectively remove the noise and enhance the local features, edges and image contrast without losing any relevant information in the original mammogram image [21], [22]. However, the performance of the standard CLAHE technique depends on two key parameters: clip limit (c) and block size (b) and these parameters values were heuristically chosen by users [18], [19], [20], [21], [22].

A few studies attempted automatic tuning of CLAHE parameters. Abbas et al. [23] proposed a breast mass segmentation technique using 4-stage multiscale system. In the study, authors have used CLAHE for contrast improvement and the clip limit was adaptively determined by subtracting the standard deviation of the pixels in the neighborhood from the maximum histogram value in that window. In their algorithm, the block size 16×16 pixels was determined experimentally. Bhat et al. [24] implemented ACL-CLAHE using Least Mean Square algorithm on a digital signal processor hardware for enhancement of medical images. In their study an optimum window size was selected according to statistical metrics like Absolute Bright Mean Square error and Peak Signal to Noise Ratio. Even though above studies have used ACL-CLAHE, it may be difficult to use these techniques for improvement of the segmentation of masses in local dense background. Table I top panel and Figure 6 shows the performance comparison for mass segmentation in local dense background between ACL-CLAHE based on standard deviation and proposed ACL-CLAHE. ACL-CLAHE using Least Mean Square algorithm [24] is not used for comparison, since it is a hard based approach.

In this paper, an ACL-CLAHE based on entropy is proposed. The aim of this study is to improve the segmentation of masses in local dense background. That is breast lesions with high intensity value (Bright region) superimposed on background with similar intensity. To show that the proposed method improves the performance in local dense background without compromising the performance in local non-dense background, two categories of images were used. Those with masses located in local dense background and those with masses in local non-dense background. The standard CLAHE heavily depends on the clip-limit c and block size b which are user defined. In this study these two parameters are determined adaptively for each image by using an optimization algorithm which utilizes the measure of entropy. To analyze the effect of the proposed enhancement method on mass segmentation, Fuzzy C-means (FCM) clustering followed by morphological filling is used to produce mass candidates. The proposed ACL-CLAHE enhancement performance is compared with other commonly used enhancement techniques. The results are evaluated using the Dice index.

III. Materials and Methods

The mass segmentation algorithm using proposed ACL-CLAHE consists of three steps: contrast enhancement using proposed ACL-CLAHE, Fuzzy C-Means Clustering and extraction of best mass candidate. Figure 1 shows the flow chart for mass extraction.

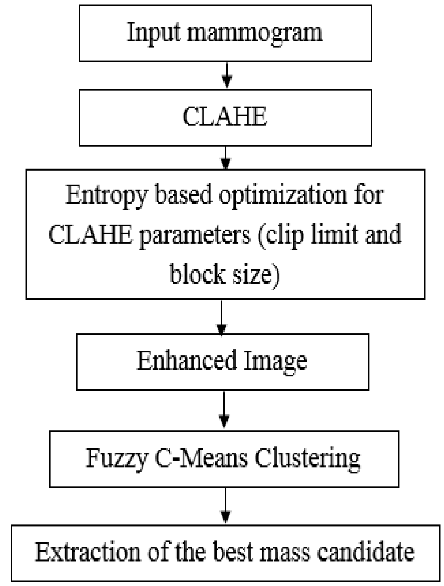


Fig. 1: Flow chart for mass extraction

A. Database

For this study, images were selected from the publicly available Digital Database for Screening Mammography (DDSM) [25]. DDSM have used four scanners: DBA M2100 ImageClear (42×42 microns per pixel, 16 bits), Howtek 960 (43.5×43.5 microns per pixel, 12 bits), Lumisys 200 Laser (50×50 microns per pixel, 12 bits), and Howtek MultiRad850 (43.5×43.5 microns per pixel, 12 bits). The database contains 2620 mammogram images in 43 volumes. Out of 43 volumes in DDSM, only 15 volumes contain cancer. From those 15 volumes, 41 images having malignant mass in local dense background and 48 in local non-dense background were identified and employed in this study. The local dense background in this study refers that the mass is overlapped with fibroglandular tissues having similar intensities with the mass. This division of local dense and non dense background is not same as Breast Imaging-Reporting and Data System (BI-RADS) [26] category.

BI-RADS classify breast density according to the overall spread of fibrous and glandular tissues. Figure 2 illustrates the difference of mass in local dense and non dense background with BI-RADS category. Mammogram in top right shows mass in local non-dense background though the breast density is high (BI-RADS III-IV) and bottom left shows mass in local dense background though breast density is low (BI-RADS I-II). Mass annotations are provided in the DDSM database, however most of the masses are annotated with a generous boundary and do not trace the detailed outline of the mass. Therefore, core mass contours were manually delineated for each image by one of the authors (S.S) as directed by an experienced radiologist in mammography. One example is shown in Figure 3. ImageJ software package [27] was used to draw the contours. To reduce the computational time, images were down-sampled by a factor of 8.

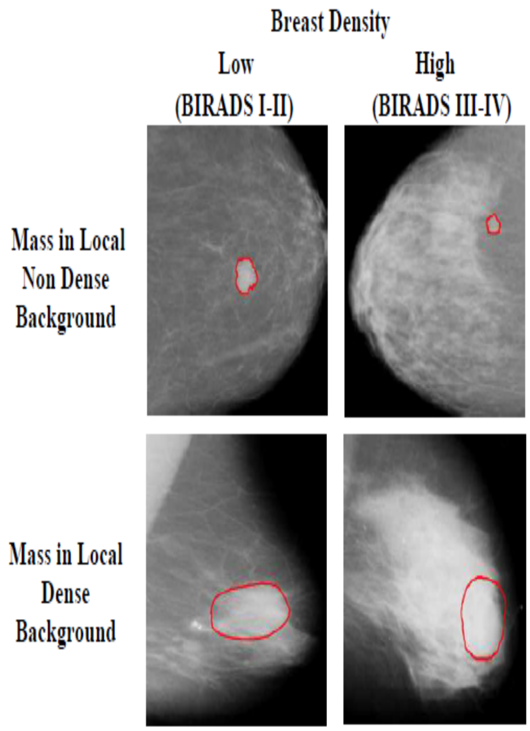


Fig. 2: Examples of mammograms showing masses in local non-dense and local dense background. Top row shows mass in local non-dense background and bottom row, mass in local dense background. Top right shows mass in local non-dense background though the breast density is high and bottom left show mass in local dense background though breast density is low.

B. *Proposed ACL-CLAHE*

In mammograms, masses are usually hyperdense with respect to background. This makes the detection of masses in local dense background more difficult. The CLAHE technique have the potential to improve the contrast of mammographic masses from the surrounding tissues [19], [21], [22]. However, the major concern with CLAHE is the selection of parameter values, whose selection play an important role in order to achieve best image enhancement. Automatic tuning of the parameters values to yield enhanced image is a difficult task. In this paper, we have proposed an ACL-CLAHE with self-adjusted clip limit and block size to improve the segmentation of masses in local dense background.

1) CLAHE: Histogram equalization (HE), which stretches the dynamic range of intensity, is one of the most popular methods for enhancing the contrast of image [16]. The standard procedure is to remap gray scales of input image to an output image, so that the resultant histogram approximates that of the uniform distribution. Even though HE have the advantage of

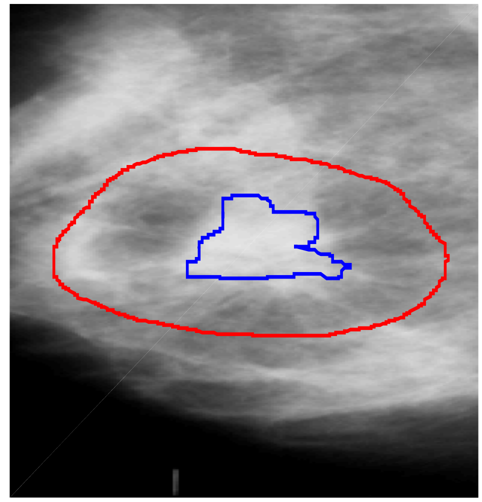
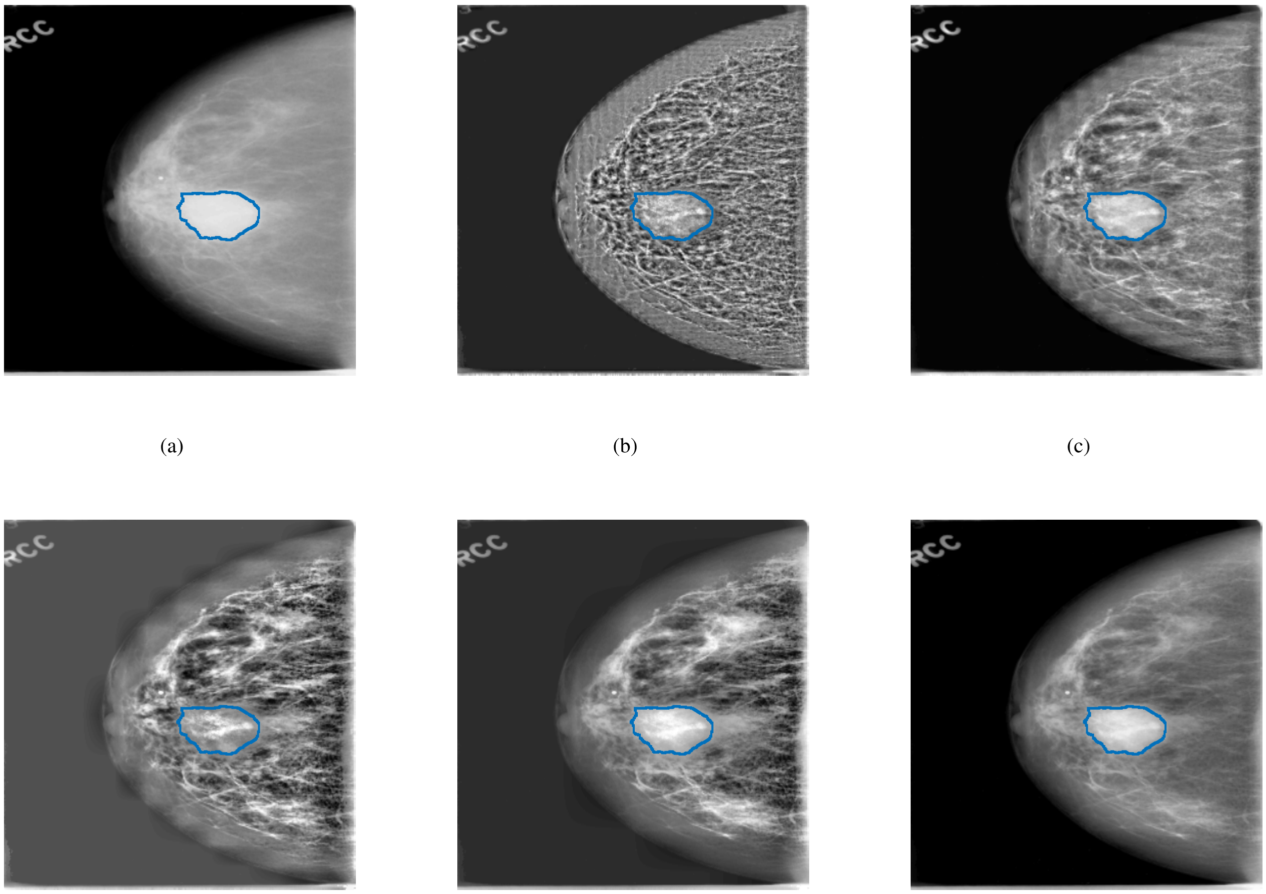


Fig. 3: ROI with DDSM mass contour (in red) and by author S.S (in blue)

high speed, in many cases it produces over enhancement and loss of local information which leads to insufficient medical details during diagnosis. Compared with standard HE, AHE has the advantage of improving local contrast by computing several histograms, corresponding to distinct sections of the image, and using this to redistribute the intensity values of image. However, it suffers from high computation time and noise amplification. The noise amplification can disturb the local details of the image. In order to overcome this limitation, CLAHE a variant of AHE which reduces the noise amplification was proposed [28], [29]. CLAHE limits the amplification by clipping the histogram at a user-defined value called clip limit and this clip limit determines how much noise in the histogram should be smoothed and hence how much contrast should be enhanced. CLAHE equally redistributes the histogram above clip limit among all the histogram bins. The histogram can have different distributions such as uniform, exponential, Rayleigh etc. A uniform probability density distribution does not help in the mass detection in dense region, as it simultaneously distribute the dynamic range between background and foreground. Therefore, Rayleigh distribution which is a nonuniform distribution function is used in this study. Finally cumulative distribution function is determined for the gray scale mapping where the mapping at each pixel is interpolated using bi-linear interpolation of the neighboring pixels.

Even though CLAHE with Rayleigh distribution gives good contrast enhancement for mammogram images, it heavily depends on the clip limit and block size. These parameter values are set up by the user. When a user determines inappropriate parameters values, the results of the CLAHE may be worse than that of original image. Figures 4 shows an example of CLAHE with different clip limit and block size. The results shows that inappropriate selection of clip limit and block size may not improve the result (see Figure 4



(a) (b) (c)

(d) (e) (f)

Fig. 4: Example of CLAHE with different Clip Limit and Block Size (a) Original image (b) CLAHE (c=0.1, b=8×8) (c) CLAHE (c=0.02, b=16×16) (d) CLAHE (c=0.3, b=32×32) (e) CLAHE (c=0.1, b=64×64) (f) CLAHE (c=0.008, b=64×64)

(b) and (d)) while proper selection can significantly improve the result (see Figure 4 (f)). In un-enhanced image mass located in a local dense background is hardly visible and the boundaries are extremely hard to detect (See Figure 8 (a)). This can cause failure of mass detection in original image due to under segmentation, while CLAHE with proper parameter setting can provide better noise removal and enhance contrast between mass and background which can help in proper mass segmentation (See Figure 8 bottom row).

The parameters clip limit and block size controls the contrast of the image and hence the quality of enhancement. In most applications of the CLAHE algorithm, clip limit and block size are fixed empirically for a class of images with the result that is far from the optimal for some members of the class. In this paper, clip limit and block size are adjusted automatically for each image by optimizing the measure of entropy which is described in the next section.

2) Entropy of enhanced image: Adjusting the parameters values without human intervention is a difficult task in image processing. This is because automatic image enhancement requires specifying an objective criterion for enhancement and this objective criterion should adjust the quality of the image for the particular task. It is widely accepted that some breasts appear in mammograms with very few features as they have little dense tissue which could be interpreted as mass-like, while some others contain a variety of intensity variation and many mass-like regions [8]. In both cases, a better segmentation results, if a good balance is reached between the overall variation of image intensity and variation associated with mass-like regions. This can be achieved by measuring the image entropy [30], [31]. In [30], a region based measure of entropy is used to delineate large objects in mammograms. In [31], the authors showed on natural scene images that the parameters clip limit and block size of CLAHE determined at the point with maximum entropy curvature can produce subjectively good quality of the image.

This study of automatically tuning the clip limit and block size of CLAHE using a measure of entropy was motivated by above mentioned works. Based on the histogram, the entropy value was calculated on the enhanced image I_e as given below [32]

$$H(I_e) = -\sum_{i=1}^{n} h_i log_2 h_i \qquad (1)$$

where h_i is the probability occurrence of the intensity value in the enhanced gray image I_e.

3) Optimization Algorithm: To determine optimal values for the clip limit (c) and block size (b) the following algorithm was followed. Every mammogram was enhanced using CLAHE with a limited range of values of c and b. For each value of c and b, the entropy of the enhanced image was computed using Equation 1. The value of c and b resulting in the maximum difference in entropy were selected as optimal parameter values for the enhanced image. The reasonable range for c was (estimated experimentally) selected as $0.001 : 0.001 : 0.02$, and block size 16×16, 32×32, 48×48 and 64×64 were tested.

C. Fuzzy C-Means Clustering

In mammographic image analysis, it is essential to distinguish the suspicious region from its surroundings. Segmentation process is the method usually used to separate the region of interest from the background. Clustering methods help to segment the image. To demonstrate the effectiveness of automatically optimized clip-limit and block size of CLAHE, FCM clustering algorithm was adopted. FCM clustering is one of the most popular algorithms for segmentation. FCM uses iterative optimization of an objective function based on weighted similarity measures between the pixels in the image and each cluster center [33]. In this study, for FCM algorithm, 10 classes were used to determine the mass candidate.

D. Mass Candidate Selection

Masses are usually hyper-dense with respect to its background with core parts having high intensity values which tend to decrease as the distance to core parts increases [33]. This property is preserved with the proposed enhancement algorithm. This allows morphological filling to be utilized to get a good mass like component, as shown in Figure 5. The figure shows the mass in FCM clustered image. It can be observed that the mass with an inner core having high-intensity which decreases as the distance to core increases. This high intensity region of the mass is identified as a single core component with the outer area being another component. Morphological filling is used to obtain mass like components. The component whose 80% of the area residing inside of the annotated region (ground truth) with the highest Dice index is accepted as the mass region.

E. Performance Measure

The performance measure used is Dice index and it is one of the most popular similarity measures for sets. The Dice index for two sets is calculated as follows [34]

$$DICE(X,Y) = \frac{2 \mid X \cap Y \mid}{|X| + |Y|}$$

where X and Y are the two sets to be measured. It is calculated by simply taking twice the number of elements common to both sets divided by the total number of elements in the two sets. The Dice index value ranges between 0 and 1. A value of 0 indicates that two sets have no common elements and value 1 indicates that the segmentation result and ground truth overlap entirely.

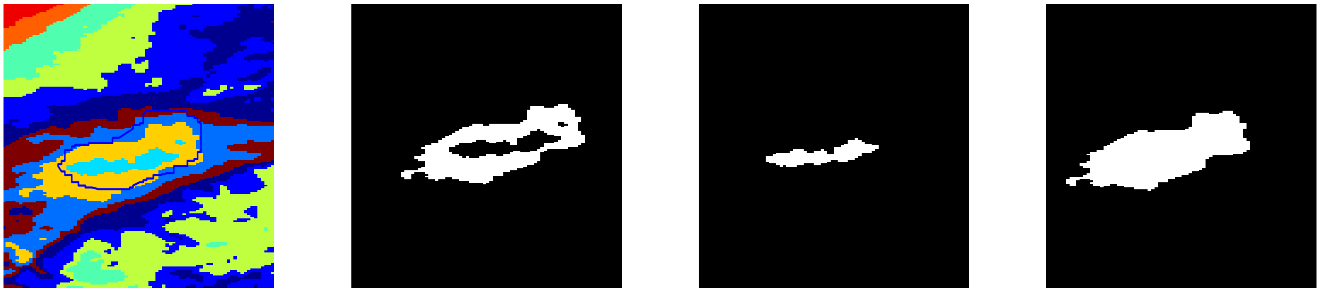
TABLE I: Performance comparison for mass segmentation using Dice index for the DDSM set for both mass in dense background (41 images) and non-dense background (48 images) for each of the seven methods. Column 2 is the percentage of the number of images whose dice index is greater than 0.5. The corresponding number of images is shown in brackets.

Mass in dense background	
Approach	Dice Index (0.5+)
original (no enhancement)	51%(21)
Adjustable HE	56%(23)
UM	54%(22)
neutrosophic	56%(23)
CLAHE	88%(36)
ACL-CLAHE (std)	78%(32)
proposed ACL-CLAHE	**95%(39)**
Mass in non-dense background	
Approach	Dice index (0.5+)
original (no enhancement)	81%(39)
Adjustable HE	83%(40)
UM	81%(39)
neutrosophic	88%(42)
CLAHE	96%(46)
ACL-CLAHE (std)	90%(43)
proposed ACL-CLAHE	**98%(47)**

IV. Results and Discussion

The performance of the proposed ACL-CLAHE is compared with six enhancement techniques: Adjustable Histogram Equalization [35], traditional Unsharp Masking (UM) , Neutrosophy based enhancement [36], standard CLAHE, ACL-CLAHE based on standard deviation [23] and original image with no enhancement. For the enhancement techniques, the best parameters values were determined empirically. For mass in local dense background, the parameters values for Adjustable HE (sigma), UM (scaling factor), CLAHE (clip-limit and block-size), ACL-CLAHE (block-size) and Neutrosophy (alpha and beta) were 0.6, 0.7, 0.013, 64×64, 64×64, 0.85 and 0.85 and for mass in local non dense background were 0.2, 0.5, 0.01, 64×64, 64×64, 0.85 and 0.85 respectively.

Table I shows the performance comparison for mass segmentation using Dice index for both mass in local dense and local non-dense background. The results demonstrate that the mass segmentation performance with proposed ACL-CLAHE enhancement is significantly better than those of the other six methods. With the proposed method, 95% of the images were segmented with a high dice index for mass in local dense background and 98% for mass in local non-dense background. It shows an increase of 44% for mass



(a) (b) (c) (d)

Fig. 5: Mass candidate segmentation with morphological filling (a) ROI showing the location of the mass (b) Outer component of the selected mass candidate (c) Inner component (d) Single mass component after applying morphological filling

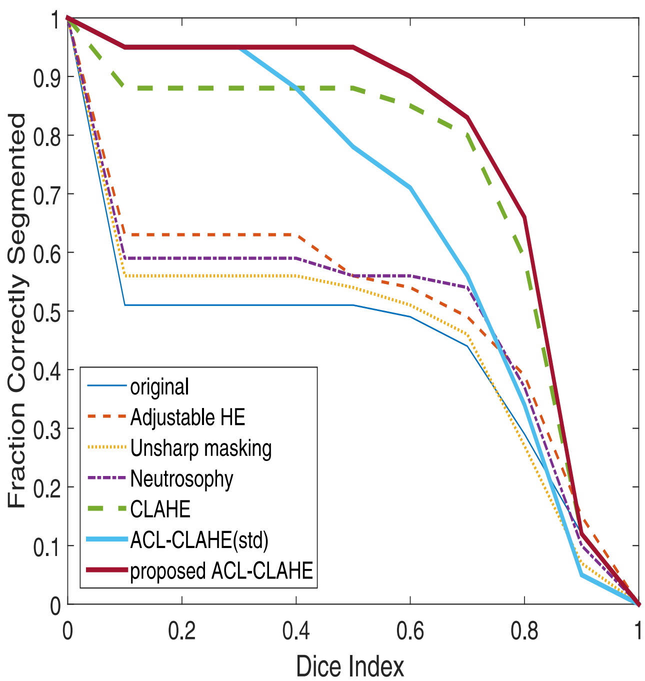


Fig. 6: Performance comparison for mass segmentation in local dense background with seven different image enhancement methods

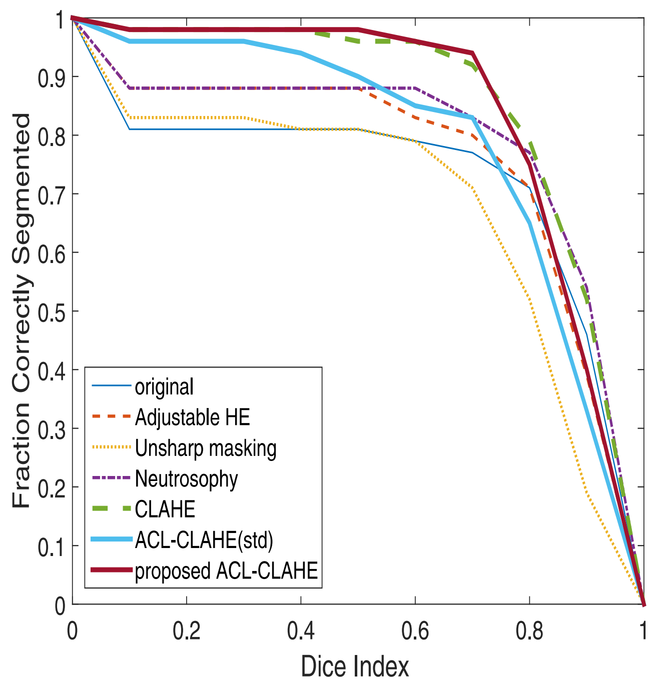


Fig. 7: Performance comparison for mass segmentation in local non-dense background with seven different image enhancement methods

segmentation (Dice index greater than 0.5) in local dense background and 17% for mass segmentation in local non-dense background in comparison to original image with no enhancement. In general, CLAHE group (Standard CLAHE, ACL-CLAHE using standard deviation and proposed method) showed considerably superior results than non CLAHE methods (Adjustable HE, UM, Neutrosophy based enhancement and original image with no enhancement) for mass segmentation in local dense background. Comparing with standard CLAHE and ACL-CLAHE using standard deviation, the proposed method showed an increase of 7% and 17% respectively. Even for mass segmentation in local non-dense background, the proposed method is better compared to all others. Figures 6 and 7 show plots of the proportion of the correctly segmented masses as functions of Dice index. These plots also indicate that the proposed ACL-CLAHE method, utilizing entropy performance is significantly better than other commonly used enhancement methods.

Figure 8 shows the impact of the proposed ACL-CLAHE for mass delineation in comparison with original image with no enhancement for mass in local dense background. The top row shows the process of obtaining the mass candidate for unenhanced image and the bottom row shows the same for the proposed ACL-CLAHE enhanced image. It is evident from the original image (See Figure 8 top row (a)) that the mass is hardly visible and the boundaries are extremely hard to detect.

Figure 8 demonstrates that the proposed method is found to be effective in segmenting such hard cases while mass candidate is lost in original image due to under segmentation.

In addition to all, the automatic parameter selection capability of proposed ACL-CLAHE provides a superior advantage by removing the manual efforts and reducing the accuracy issues. The performance of ACL-CLAHE based on standard deviation is considerably below than proposed method for both mass in local dense background and local non-dense background. Out of the 41 cases of masses in local dense background and 48 cases of masses in local non-dense background, only in 3 cases the proposed ACL-CLAHE was not able to detect reasonable mass candidate. A close inspection of the 3 cases in which the proposed algorithm was not able to segment a reasonable component revealed the following details. In one case, from non-dense background, the component had a small tail connecting to another region which causes the failure. A good mass component with 0.87 Dice Index could be achieved by applying morphological erosion with structuring element of size 1. In the other two cases from dense background the masses did not have a noticeable central core region. Similar failure cases have been reported in paper [37]. Other methods such as temporal analysis [38] or left and right breast comparison [39] may help in these cases.

V. Conclusion

In this study, a technique utilizing an entropy measure for tuning the clip limit and block size of CLAHE is proposed for improving the mass segmentation in local dense background. The proposed method has been tested on 89 mammograms and compared with the existing popular enhancement approaches. Experimental results show that proposed ACL-CLAHE enhancement algorithm has the potential to improve the mass candidate segmentation in local dense background of mammograms. This improvement on local dense background is achieved while retaining high performance level on local non dense background. Moreover, automatic parameter selection capability of proposed ACL-CLAHE provides a significant advantage over standard CLAHE by removing the manual efforts. A potential direction for future work is to develop a fully automated CAD system to provide early detection of breast masses in local dense background using proposed ACL-CLAHE enhanced mammograms.

VI. Acknowledgments

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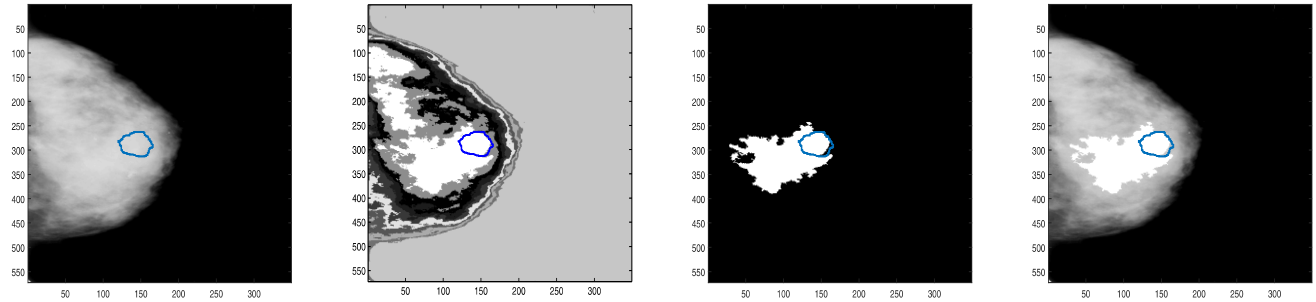
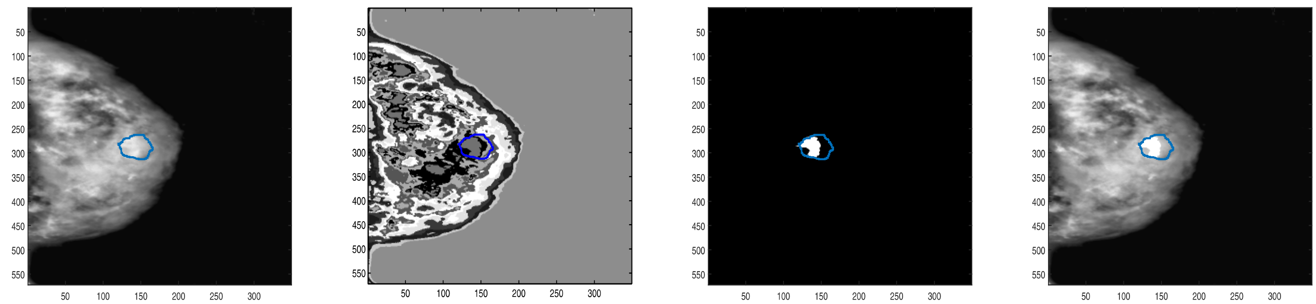


(a) (b) (c) (d)



(e) (f) (g) (h)

Fig. 8: The impact of the proposed ACL-CLAHE for mass delineation, first row shows the process of obtaining the mass candidate for unenhanced image and the second row shows the same for the proposed ACL-CLAHE enhanced image, (a) and (e) Original and enhanced image with core mass contour, respectively (b) and (f) Segmented image after applying FCM, (c) and (g) mass candidate detected inside the ground-truth for unenhanced and enhanced image, respectively and finally (d) and (h) mass candidate superimposed on original and enhanced image respectively

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