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Review: On Performance Metrics for Quantitative Evaluation of Contrast Enhancement in Mammograms

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ABSTRACT

The most common cancer of women is breast cancer which is the leading cause of cancer-related death among women aged 15 to 54. The risk of cancer increases after the age of 40's. Thus earlier detection of breast cancer increases the probability of survival of the patient. For its detection mammography is done, but many of the masses remain either undetected or falsely detected due to poor contrast and noise present in mammographic images. Thus for earlier detection of cancerous masses many enhancement techniques are applied. In this paper various set of performance metrics that measure the quality of the image enhancement of mammographic images in a CAD framework that automatically finds masses using machine learning techniques. These performance metrics quantitatively measures the best suited image enhancement on a per mammogram basis, which improves the quality of ensuing image segmentation much better than using the same enhancement method for all mammograms.

Keywords
MLO, CC, ASNR, PSNR, ROI, DSM, CEM, CII, CD, TBC_s, TBC_e.

1. INTRODUCTION

Breast cancer relates to the growth of malignant in the cells of breast tissue. Normally the generation i.e. formation, growth, division and regeneration of the tissues in breast take place continuously in an ordered way. But when this control fails there is tumour formation. The time span for the evolution and growth of the tumour differs between individuals. As in other cancers it spreads to other tissues thus causing dissemination of cancer. So early detection and treatment can minimize this phenomenon and give a better diagnosis for the patient. Few risk factors of breast cancer are age (more prominent above 50 years), abnormal cells in fibrocystic disease, family history of patient, any hormone replacement therapy if done, previous breast cancer, null parity and chest radiation exposures, early menarche, obesity and late menopause.

Fig. 1: Stages of cancer from Normal to Benign and Malignant [1]

Asymmetry between breasts and some characteristic lesions like micro-calcifications, masses and architectural distortions are indicator of breast cancer. Micro-calcifications are small in size thus hard to detect. Its size ranges from 0.05 to1 mm. They can be of various size, shape and distribution. An accurate detection of micro-calcification is very essential for detection of most of the breast cancers. All the researches done with CAD on mammograms deals with two things: (i) Detection of calcification [2][3][4][5][6][7][8][9][10][11][12] and (ii) Detection of suspected mammographic masses [13][14][15][16][17][18][19][20][21][22][23][24].

1.1 Breast Cancer Lesions

Generally smaller, irregular, polymorphic and branching calcification with heterogeneous morphology and size have higher probability of being malignant while larger, oval shaped or round calcification with uniform size have higher probability of being benign [25].

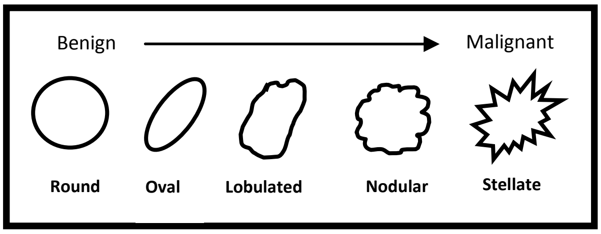


Fig. 2: Morphologic spectrum of mammographic masses

Masses have different malignant probability depending on their morphology. Like masses with uneven, spiculated and ill-defined borders have more probability of malignancy. Thus the variable shape of masses in mammograms creates problems in their detection.

1.2 Mammography

Mammography is the most reliable and efficient method for detection of clinically occults illness. If done earlier can prevent the disease to get potentially hazardous. Mammography is high resolution X-ray imaging of the compressed breast. As the density of the increases the efficiency of the mammography decreases. Thus the risk of breast cancer is more in dense breasts. In Mammography low amplitude, high current X-ray (frequency ranges from 10^{16} to 10^{19} Hertz) radiations are transmitted through the tissues and the projection of anatomical structures are obtained on a film screen or image sensors. Associated with the X-ray imaging projection is a reduction in anatomical information from a 3D organ to a 2D film/image. There are two imaging projections of each breast, craniocaudal (CC) and mediolateral oblique (MLO) views, as shown in Figure 1.4.

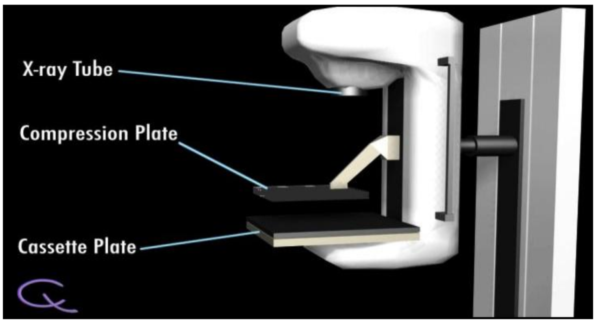
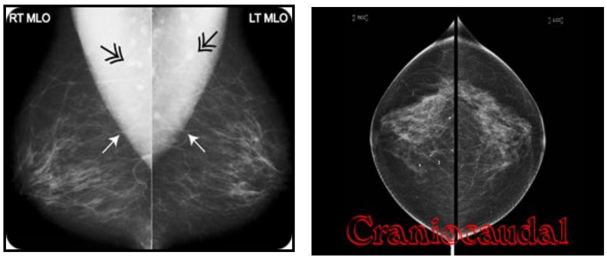


Fig. 3: Mammography machine [26]

Craniocaudal (CC), which is a view from top, allows a better imaging of the central and inner breast sectors and Mediolateral oblique (MLO), which is lateral view from certain angle gives enhanced perspective of glands.



Mediolateral Oblique (MLO) Craniocaudal (CC) view

Fig. 4: Illustration of two views taken in screening mammography [25][28]

1.2.1 *Mammography of Normal Breast*

Mammograms of normal breasts have a wide variation in appearance. The pattern of the breast which are predominantly composed of fat are often called normal if no abnormal pattern is found. Figure 1.5. shows two normal mammograms with different density of breast tissues.

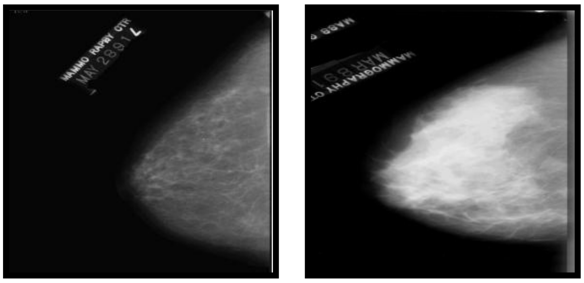


Fig. 5: (a) Predominantly fatty normal mammogram,

(b) Dense normal mammogram

High quality mammogram with high spatial resolution and adequate contrast separation allows radiologists to observe fine structures. Studies have shown that the mortality rate could decrease by 30% if all women age 50 and older have regular mammograms [27].

Normal mammograms appear with regular and undisturbed ductal patterns. Breast cancers usually appear with disturbed ductal structures. Malignant lesions generally have a more irregular shape than benign lesions. Circumscribed masses are compact and roughly elliptical. Radiolucent lesions with a halo or encapsule are usually benign.

1.2.2 *Mammography of Abnormal Breast*

Its hard to detect tiny and faint individual calcifications that are not in clusters. In most micro-calcification detection, clusters can be detected with high sensitivity, but not all the individual calcifications in the cluster. Shape and features are used to classify micro-calcifications since calcifications are usually brighter than the background and have a dot or small disc shape.

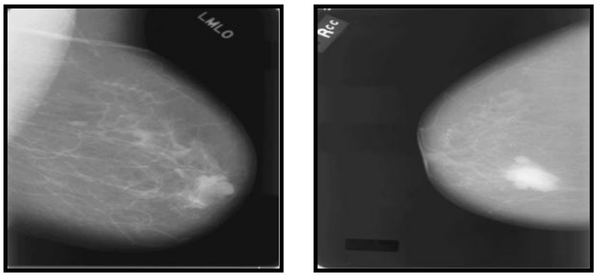


Fig. 6: (a) benign mass mammogram, (b) malignant mass mammogram

High radiopaque lesion with irregular or ill-defined boundary should be considered with a high degree of suspicion. Figure 1.6 shows a benign and a malignant mammogram. Spiculated lesions have a central tumor mass that is surrounded by a radiating pattern of linear spicules. Most spiculated lesions are malignant. Figure 1.7 shows a mammogram with a spiculated lesion.

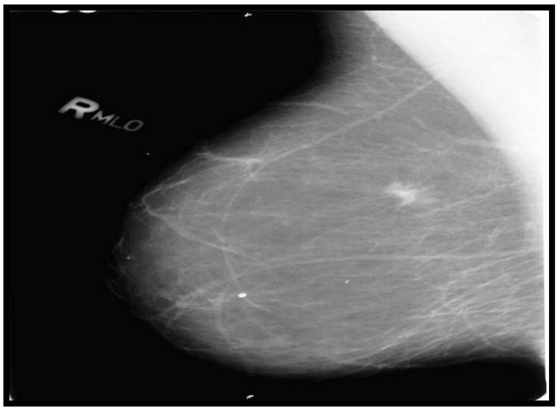


Fig. 7: Spiculated lesion mammogram

Micro-calcifications appear as bright dot-spots on screening mammograms, usually in the form of clusters. These are calcium deposits from cell secretion and necrotic cellular debris. The shape and distribution of breast calcifications indicate malignancy. There is no deterministic boundary between benign and malignant types.

2. ENHANCEMENT TECHNIQUES IN MAMMOGRAMS

Mammographic lesions like masses and micro-calcifications are very small and have low contrast from the normal breast tissue, thus they are hard to detect. Thus image enhancement can increase the subtle mass detection which leads to accurate diagnosis of the breast. False positive rates are due to low contrast, noise in the image and reduced sharpness in the feature of interest caused by overlapping of structures. Few image enhancement techniques are mentioned in the Fig 2.1.

Thus image enhancement technique includes contrast manipulation, noise reduction and edge sharpening which is used to differentiate between the region of interest (ROI) and background by increasing the contrast and sharpen the image to clearly judge the borders of abnormalities. Under enhancement can cause false negatives and over enhancement can cause false positives. Thus the quantity of enhancement is to be considered [29].

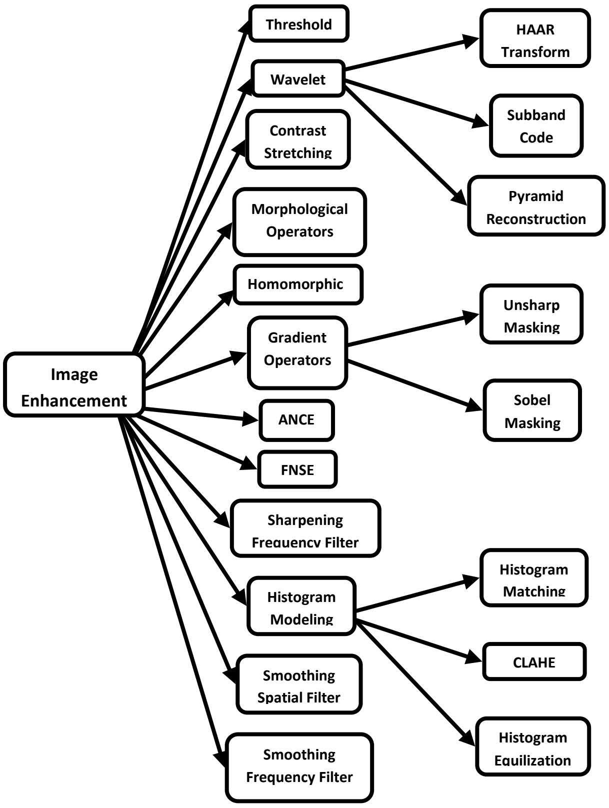


Fig. 8: Classification of some image enhancement techniques

3. PERFORMANCE METRIC FOR QUANTITATIVE MEASUREMENT OF CONTRAST ENHANCEMENT

Image enhancement refers to attenuation, or sharpening of image features such as edges, boundaries or contrast to make the processed image more useful for analysis. The greatest difficulty in image enhancement is quantifying the evaluation criteria for enhancement. Machine learning approaches are heavily dependent on the quantitative estimates of what is automatically judged to be a good image enhancement. It is, thus important to define quantitative measures for defining the quality of image enhancement that correlates well with the human expert but does not require human intervention for making such a judgment. Objective measurement of image enhancement quality is defined as when on any image I, a set of enhancement techniques $(e_1, e_2, e_3, ..., e_n)$ are applied and a set of enhanced images $(i_1, i_2, i_3, ..., i_n)$ are obtained, now a performance metric N is mathematically defined $(m_1, m_2, m_3, ..., m_n)$ within the range [0,1] that gives the spectrum of enhanced image and measures the quality of enhancement techniques applied on that image. This measurement range represents a continuous spectrum of values that each metric can take, where 0 defines the worst image enhancement and 1 represents the best enhancement [30].

A very well known objective evaluation algorithm is for measuring image quality is Peak Signal-to-Noise Ratio (PSNR) where one is accounting to measure noise suppression. But it may suffer from limitations such as accuracy, consistency and incur greater computational cost. Also it lacks a very vital feature that is the ability to assess image similarity across distortion types. PSNR may not be the final evaluation tool to evaluate the overall quality of the enhanced image, as the value of PSNR at times may get diminished (in cases of reduced noise and enhanced contrast) although the overall image assessment, subjectively appears to be good. Objective evaluation of the enhanced image is performed by using different quality metrics, such as:

3.1 Contrast Difference (CD)

Contrast difference (CD) is another objective quality measure that takes the advantages of the known characteristics of the Human Visual System (HVS) [31]. It is used for contrast comparison between the original image and the enhanced image. Michelson formula is used for measuring the contrast which depends upon the maximum and minimum intensity value of the image. According to Michelson Formula, the contrast of an image f is measured as:

$$C = \frac{f_{\max} - f_{\min}}{f_{\max} + f_{\min}} \qquad \ldots(3.1)$$

Where f_{max} and f_{min} denote the maximum and the minimum gray level intensities of a particular image f.

Hence CD can be given as:

$$CD = |C_1 - C_2| \qquad \ldots(3.2)$$

Where C_1 and C_2 are the contrast measures of the original image (f) and the transformed image (y) respectively.

3.2 Distribution Separation Measure (DSM)

In mammography, there is overlap between masses and their background border. A good enhancement technique should reduce i.e. the spread of the target distribution and shift its mean grayscale level to a higher value, thus separating the two distributions and reducing their overlap. The best decision boundary for the original image between the two classes, assuming both classes have a multivariate normal distribution with equal covariance, is given by equation (3.3), [32]

$$D_1 = \frac{\mu_B^O \sigma_T^O + \mu_T^O \sigma_B^O}{\sigma_B^O + \sigma_T^O} \qquad \ldots (3.3)$$

Similarly, the best decision boundary for the original image after enhancement is given by equation (3.4),

$$D_2 = \frac{\mu_B^E \sigma_T^E + \mu_T^E \sigma_B^E}{\sigma_B^E + \sigma_T^E} \qquad \ldots (3.4)$$

where $\mu_B^O, \sigma_B^O, \mu_T^O, \sigma_T^O$ are the mean and standard deviation of the grayscales comprising the background and target area, respectively, of the original image before enhancement. Similarly, $\mu_B^E, \sigma_B^E, \mu_T^E, \sigma_T^E$ correspond to the mean and standard deviation of the grayscales after the enhancement. If the groups are assumed to be representative of the population, a weighted average of the group centroids gives an optimal cutting score as in equation (3.5) and (3.6),

$$D_3 = \frac{\mu_B^O N_T^O + \mu_T^O N_B^O}{N_T^O + N_B^O} \quad \text{… (3.5)}$$

$$D_4 = \frac{\mu_B^E N_T^E + \mu_T^E N_T^E}{N_T^E + N_T^E} \quad \text{… (3.6)}$$

where N_B^O & N_T^O are the number of samples in the background and target before enhancement, and N_B^E & N_T^E is the number of samples after enhancement. On combining (3.5) and (3.6), distance measure between the decision boundaries and the means of the targets and background, before and after segmentation are computed. This is termed as DSM for measurement of the quality of enhancement given by the equation (3.7),

$$DSM = \left(\left|\mu_T^E - \mu_B^E\right|\right) - \left(\left|\mu_T^O - \mu_B^O\right|\right) \quad \text{… (3.7)}$$

This measurement should be greater than zero, the greater the DSM value, the better the quality of enhancement.

3.3 Target-To-Background Contrast Enhancement Measurement Based On Standard Deviation (TBC$_S$)

Objective of a contrast enhancement is to maximize the difference between background and target mean gray level and increase the homogeneity of the mass for increasing the visualization of boundaries and location. Using the ratio of the standard deviation of the grayscales within the target before and after the enhancement, the improvement can be quantified by TBC$_s$ as in equation (3.8),

$$(TBC_S) = \left\{ \frac{\left(\frac{\mu_T^E}{\mu_B^E}\right) - \left(\frac{\mu_T^O}{\mu_B^O}\right)}{\frac{\sigma_T^E}{\sigma_T^O}} \right\} \quad \text{… (3.8)}$$

where the mean and standard deviation of the grayscales of the target and background before and after the enhancement are same as DSM. This measure should also give value greater than zero [30].

3.4 Target-To-Background Contrast Enhancement Measurement Based On Entropy (TBC$_e$)

In this technique standard deviation is replaced by the entropy of the target in the original and enhanced images, ε_T^O & ε_T^E respectively, to quantify the homogeneity ratio, same as equation (3.8). Thus TBC$_e$ is given by equation (3.9),

$$(TBC_e) = \left\{ \frac{\left(\frac{\mu_T^E}{\mu_B^E}\right) - \left(\frac{\mu_T^O}{\mu_B^O}\right)}{\frac{\varepsilon_T^E}{\varepsilon_T^O}} \right\} \quad \text{… (3.9)}$$

This measure should also give value greater than zero.

3.5 Combined Enhancement Measure (CEM)

All the measures mentioned above are combined into one quantitative value. This value is thus used to quantitatively rank the enhancement techniques for a particular image. To combine DSM, TBC$_S$ and TBCe for a particular enhancement, each enhancement value is represented within a three-dimensional (3-D) Euclidean space by scaling each within the range [0,1]. The enhancement method giving the smallest value of is selected as the best enhancement method for that image. This combined enhancement measure (CEM) is given by the equation (3.9), [30]

$$CEM = \sqrt{(1 - DSM)^2 + (1 - TBC_S)^2 + (1 - TBC_e)^2} \quad \text{… (3.9)}$$

3.6 Contrast Improvement Index (CII)

In order to evaluate the enhancement results of different approaches, another set of quality metrics used are: the contrast, the contrast improvement index (CII), the background noise level (σ), the peak signal to noise ratio (PSNR) and the average signal to noise ratio (ASNR). All the computation are based on the selected local regions of interests which contain region of abnormality (masses, calcifications etc.) as well as film artifacts, in the original images obtained in the enhanced images. These indexes could be defined as follows:

The contrast C of an object is defined by [33]:

$$C = \frac{f - b}{f + b} \quad \text{…(3.10)}$$

Where f is the mean gray-level value of the particular object in the image (ROI), called the foreground and b is the mean gray-level value of the surrounding region called the background. Here the contrast of specific regions of interest is computed manually by selecting the foreground and background with the help of radiologist markings in the database. A quantitative measure of contrast enhancement can be defined by a Contrast Improvement Index (CII) [34],

$$CII = \frac{C_{processed}}{C_{original}} \quad \text{…(3.11)}$$

Where $C_{processed}$ and $C_{enhanced}$ are the contrasts of regions of interest in the processed and original image respectively.

The level of noise in the background region can be measured by the standard deviation σ in the background region which is defined as:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(b_i - b)^2} \quad \text{…(3.12)}$$

Where b_i is the gray level value of the surrounding background region and N is the total number of pixels, encompassing the background region.

If the background have large variety (i.e. noise level is high), the evaluation using only contrast (C) is not suitable, because the main purpose of enhancement is to enhance the masses and micro-calcifications, present in the inhomogeneous and variable background. Hence two new evaluation indexes are defined namely, PSNR & ASNR. These are based on general medical physics measurement and accepted by radiologists for detection of micro-calcifications.

$$PSNR = \frac{p-b}{\sigma} \quad \ldots(3.13)$$

where p is the maximum gray level value of the foreground. Similarly ASNR is defined as:

$$ASNR = \frac{f-b}{\sigma} \quad \ldots(3.14)$$

4. CONCLUSION

Since contrast in grayscale images have been lacking in robust quantitative measures because of this evaluation of the performance of different contrast enhancement methods in digital mammograms is limited. Here various performance metrics are discussed for evaluation of contrast enhancement and noise suppression in mammogram images for earlier detection of cancerous masses in breast tissues. By increasing contrast confused pixels of the image is defined either as ROI or background in digital mammograms.

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