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AN ENHANCED MAMMOGRAM DIAGNOSIS USING SHIFT-INVARIANT TRANSFORM

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Abstract
Breast cancer is a common disease for women and various techniques have been used to detect the breast cancer. The mammogram images are noise, low contrast and blur due to limitations of the X-ray hardware system. So, we should enhance the mammogram images for radiologist observation. To attain this, we strongly recognize that the digital mammography is a truthful technique with a new method and also it can easily identify the breast cancer at the very early stage before any symptoms are shown. In this paper, we propose NonSubsampled Contourlet Transform (NSCT) method for enhancing the mammogram images and the comparison between 2-D HAAR Discrete Wavelet Transform and Contourlet Transform. The NSCT extracts the shift-invariant multi-scale, multi-direction and the geometric information of mammogram images which is used to distinguish noise from weak edges than existing transformations.

Keywords:
Contourlet Transform, Discrete Wavelet Transform, Nonsubsampled Contourlet Transform, Mammogram Image Enhancement

1. INTRODUCTION

Breast cancer arises due to uncontrollably of breast cells which produce a breast tumor. The breast tumor can be normal and abnormal. The normal tumor represents no cancerous. The abnormal consists of two classes such as benign and malignant. The benign considered as a non-cancerous which is close to normal in appearance. They grow gradually and do not spread or invade nearby tissues to other parts of the body. The malignant is cancerous that spreads beyond the original tumor to the other parts of the body.

The breast has some characteristic lesions such as microcalcification and masses. The microcalcification appears with small calcium deposits and lightly brighter than surrounding tissues which is close to normal cells. The size is .33 to .7mm. It is difficult to detect them due to their small size. The microcalcification cluster is more detectable than microcalcification. The microcalcification may be benign or malignant. Benign microcalcifications are typically larger, coarse, round or oval and uniform in shape and size. Malignant microcalcifications are fine, stellate-shaped and varying in shape and size. The detection of masses are difficult because of poor image contrast. It is identified by different shapes such as round, oval, lobular and irregular with different margins. Once masses are identified it is difficult to differentiate benign or malignant but both exhibit different shape and texture. Benign masses are smooth and distinct with round in shape. Malignant masses are irregular and boundaries are usually blurry.

Several techniques have been used to detect the breast abnormalities. The mammography is a reliable method to detect breast cancer at the early stage without no symptoms. The early detection saves many lives and reduces mortality rates.

There are two types of 2-D mammography: digital mammography and film mammography. In digital mammography, X-ray beams are captured by specially designed camera and computer to produce image about breast characteristics for the radiology observation. In film mammography, X-ray beams are recorded into films and special X-Machines produce the image to analyze breast characteristics for radiologist observation.

2. LITERATURE REVIEW

Several algorithms have been used to enhance the mammogram images. They are classified into two categories: frequency domain and spatial domain methods. The frequency domain method decomposes the mammogram image into different components in the frequency domain whereas spatial domain method employs on pixel levels to modify the image brightness, contrast or the distribution of the grey levels.

2D Discrete Wavelet Transform (DWT) decomposes an image into two components such as average components and detail components. Microcalcification edges are enhanced using discrete wavelet transform by separating the wavelet coefficients into weak and strong edges. These edge coefficients are modified based on the energy coefficients to obtain better enhanced mammogram images[1].

Contourlet Transform (CT) decomposes mammograms into a multi-scale sub-band representation [2], [3]. Next, the transform coefficients in each sub-band of the multi-scale representation are modified using different technologies, including nonlinear filtering, regression-based extrapolation, the wavelet shrinkage function and directly contrast modification. Finally, the enhanced mammograms can be obtained from the modified coefficients.

Fuzzy logic has also been successfully integrated with other techniques such as histogram equalization for enhancing medical images [4], and structure tensor for contrast enhancement of microcalcifications in digital mammograms.

Karen Panetta [5] describes a Non Linear Unsharp Masking (NLUM) for mammogram enhancement. In this approach the resulting image will be more sharper than the original image by combining the unsharp mask with the negative of the image. The goal of HE is to modify the histogram in order to acquire a uniform histogram for the enhanced image [6]. An Adaptive

Histogram Equalization (AHE) the intensity of each pixel is mapped to a value determined by calculating the histogram of a window centered at that pixel. Adaptive neighborhood contrast enhancement (ANCE) has been used to improve the contrast of specific regions, objects, and details in mammograms based on local region background and contrast [7]. Contrast-Limited Adaptive Histogram Equalization (CLAHE) method splits the mammogram images into contextual regions and applies the histogram equalization for each region to enhance the mammogram images [8].

Several techniques have been used to measure the performance image enhance algorithms. A good image enhancement algorithm should increase the foreground details of the image but not the background details. The measure of enhancement (EME) and the measure of enhancement by entropy (EMEE) have been developed based on a Weber-law-based contrast measure [9]. The performance of the EME and EMEE have been improved by the Michelson law measure of enhancement (AME) and Michelson law measure of enhancement by entropy (AMEE)[10]. In this paper, we use Distribution Separation Measurement (DSM) and Target to Background Contrast Enhancement Measure (TBC) to evaluate the performance of the mammogram enhancement [11].

3. MAMMOGRAM ENHANCEMENT

The screened mammogram images may contains low resolution or low contrast due to their small size, different shapes and limitations of X-ray hardware system. It is difficult to detect the breast cancer at the early stage. This shows poor quality image for the radiologisty'observation. So, we have to enhance the mammogram images to produce improved visual quality. In this section briefly discuss the proposed method with Haar 2D DWT and contourlet Transform.

3.1 HAAR 2D DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) is a very useful tool for signal processing and image processing, especially in multi-resolution domain. It decomposes an image into different components in the frequency domain. One-Dimensional DWT decomposes an input image into two components, average and detail components. 2D-DWT decomposes an image into four components, one average component and three detail components. The three detail components are Low-High (LH), High-Low (HL) and High-High (HH) as shown in the Fig.1.

In image processing, 2D DWT has been used to detect edges of original images. Traditional methods are also used to detect edges. 2D DWT detects three kinds of edges but traditional methods cannot detect three kinds of edges. The traditional methods processing time is also slower than 2D DWT.

There are three kinds of edges present in the detail component with little coefficient. 2-D filter with Haar DWT used to detect edges with better coefficients and the processing time also decreases. It has been widely used especially in multi-resolution. The Haar DWT has the following advantages: 1) It is real, orthogonal and symmetric. 2) It can be used to analyze texture and detect edges of charateristics 3). The low-pass and high-pass filter coefficient is simple (either -1 or 1).

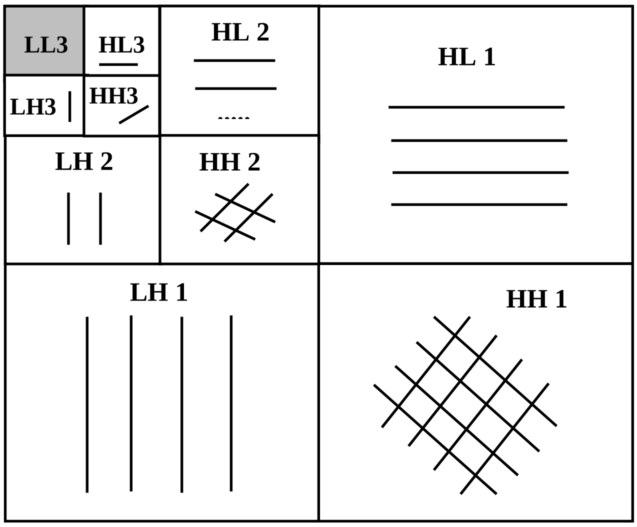


Fig.1. DWT Image Decomposition

In the Haar 2D DWT multi-scale processing, the input image decomposes into k scales. Uniform contrast measure [12] is applied to modify the coefficients to enhance the mammogram images in all the sub-bands at k^{th} scale, then the image is reconstructed. We use the following notations to enhance mammogram images:

- $I(i, j)$ denotes an input image
- $H_0(n)$, $H_1(n)$ and $G_0(n)$, G_1 (n) represent analysis filters and synthesis filters
- A_k, H_k, V_k, and D_k refers approximation of LL sub-band, horizontal, vertical and diagonal components at the k^{th} respectively.

3.1.1 *Image Decomposition:*

The K levels decomposition using Haar 2D DWT into four sub-bands are performed as follows:

$$\begin{aligned} A_k(i, j) &= \sum\nolimits_{m,n\in z} H_0(m)H_0(n)A_{k-1}(2i-m, 2j-n) \\ H(i, j) &= \sum\nolimits_{m,n\in z} H_0(m)H_1(n)A_{k-1}(2i-m, 2j-n) \\ V(i, j) &= \sum\nolimits_{m,n\in z} H_1(m)H_0(n)A_{k-1}(2i-m, 2j-n) \\ D(i, j) &= \sum\nolimits_{m,n\in z} H_1(m)H_1(n)A_{k-1}(2i-m, 2j-n) \end{aligned} \quad (1)$$

3.1.2 *Image Reconstruction:*

The reconstruction from the sub-bands can be expressed as:

$$A_{k-1}(i, j) = 4 \times \begin{bmatrix} \sum\limits_{m,n\in z} G_0(m)G_0(n)A_k\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \\ +\sum\nolimits_{m,n\in z} G_0(m)G_1(n)H_k\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \\ +\sum\nolimits_{m,n\in z} G_1(m)G_0(n)V_k\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \\ +\sum\nolimits_{m,n\in z} G_1(m)G_1(n)D_k\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \end{bmatrix} \quad (2)$$

3.1.3 *Direct Contrast Enhancement:*

The local contrast for each directional sub-band is defined as follows:

- Vertical contrast: $VC_k(i,j) = \dfrac{V_k(i,j)}{A_k(i,j)}$
- Horizontal contrast: $HC_k(i,j) = \dfrac{H_k(i,j)}{A_k(i,j)}$
- Diagonal contrast: $DC_k(i,j) = \dfrac{D_k(i,j)}{A_k(i,j)}$

The mammogram is enhanced through applying the following steps:

1) At scale k the enhanced sub-bands are obtained as follows:
   - $\overline{A_k}(i,j) = A_k(i,j)$
   - Enhanced vertical sub-band: $\overline{V_k}(i,j) = \lambda V_k(i,j)$
   - Enhanced horizontal sub-band: $\overline{H}(i,j) = \lambda H_k(i,j)$
   - Enhanced diagonal sub-band: $\overline{D}(i,j) = \lambda D_k(i,j)$

   where, λ denote the contrast manipulation factor.
2) At scales $s = k$-1, k-2… 2, iterate the following steps:
3) Obtain the enhanced image:

$$\bar{I}(i,j) = 4 \times \left[\begin{array}{l} \sum_{m,n \in z} G_0(m) G_0(n) \overline{A_2}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \\ + \sum_{m,n \in z} G_0(m) G_1(n) \overline{H_1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \\ + \sum_{m,n \in z} G_1(m) G_0(n) \overline{V_1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \\ + \sum_{m,n \in z} G_1(m) G_1(n) \overline{D_1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \end{array} \right] \quad (3)$$

This transform provides an improved result than existing 2D DWT but which is bounded by some limitations such as obtaining an efficient extraction of smooth contours and geometric structures in images.

3.2 CONTOURLET TRANSFORM

The pitfalls faced in the case of the Haar 2D DWT has been resolved by Contourlet Transform (CT). This transform has been constructed by Laplacian pyramid (LP) and Directional Filter Banks (DFB). The multi-scale decomposition is achieved by LP and directional decomposition is handled by DFB. The LP captures the point discontinuities and then followed by DBF to link the discontinuities into linear structure.

First input image consists of components like LL (Low Low), LH (Low High), HL (High Low) and HH (High High).The LP produce Low pass output (LL) and band pass (LH, HL, and HH) output at each level. The band pass output is passed to DFB, which results in CT coefficients. The low pass output is again passed through the LP to obtain more coefficients and this process is continued until the fine details of the image are retrieved. This process is shown in Fig.2.

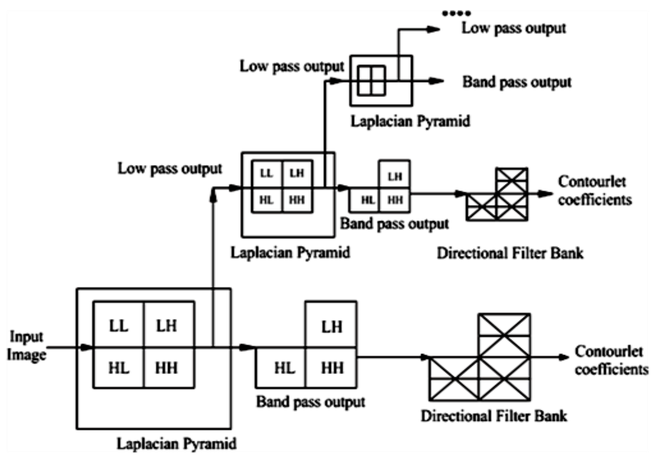


Fig.2. Architectures of CT

The breast lesions are difficult to detect due to their small size, poor contrast, noisy and blurry. In this transform, the pixels are classified into two types such as strong edges and faint edges. The strong edges are easy to detect but faint edges are difficult to detect due to their thin lesions. So we have to soften the strong edges and amplify the faint edges. To obtain this, the CT coefficients are modified by nonlinear function y_α .The edges are enhanced based on the following equations.

$$\begin{array}{ll} y_\alpha(x,\sigma) = 1 & if\ x < \alpha\sigma \\ y_\alpha(x,\sigma) = \dfrac{x-\alpha\sigma}{\alpha\sigma}, \left(\dfrac{t}{\alpha\sigma}\right)^q + \dfrac{2\alpha\sigma - x}{\alpha\sigma} & if\ \alpha \le x < 2\alpha\sigma \\ y_\alpha(x,\sigma) = \left(\dfrac{t}{x}\right)^q & if\ 2\alpha\sigma \le x < t \\ y_\alpha(x,\sigma) = \left(\dfrac{t}{x}\right)^s & if\ x \ge t \end{array} \quad (4)$$

where, σ is a noise standard deviation, t is a degree of nonlinearity and s is a dynamic range compression. Using a nonzero s will enhance the faintest edges and soften the strongest edges. α is a normalization parameter. The t parameter is the value under which coefficients are amplified. This value depends obviously on the pixel values. Here, t is two options are possible:

- $t = F_{t\sigma}$, where σ is standard noise deviation and F_t is an additional parameter which is independent of the Contourlet coefficient values.
- t = l $M\alpha$, with l < 1, where $M\alpha$ is the maximum Contourlet coefficient of the relative band.

Pseudo code

Step 1: Read input mage.

Step 2: Extract ROI (256 × 256) image I from input image.

Step 3: Calculate the noise standard deviation σ of image I.

Step 4: Set of sub-bands V_j, each band V_j contains N_j coefficients $C_{j,k}$ ($k \in [1,N_j]$) and corresponds to a given resolution level.

Step 5: Calculate the noise standard deviation σ_j for each band j of the Contourlet transform.

Step 6: For each band V_j do

1) Calculate the maximum value M_j of the band.

2) Multiply each Contourlet coefficient $C_{j,k}$ by $y_\alpha(| C_{j,k} | \sigma_j,)$.

Step 7: Reconstruct the enhanced image from the modified Contourlet coefficients.

3.3 NONSUBSAMPLED CONTOURLET TRANSFORM

NonSubsampled Contourlet Transform (NSCT) is completely shift-invariant transform which consists of both NonSubsampled Pyramid (NSP) handling multi-scale property and NonSubsampled Directional Filter Bank (NSDFB) providing directionality [13]-[16].

In this algorithm, first the NSP splits the image into a high-frequency sub-band and a low-frequency sub-band then the high-frequency sub-band is split into various directional sub-bands by a NDFB. The process is repeated on the low-frequency sub-band as shown in the Fig.3.

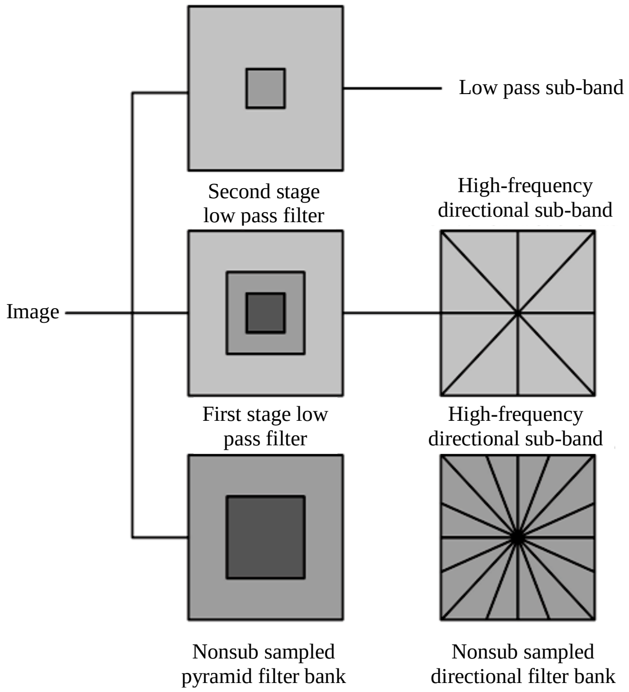


Fig.3. NSCT Process - NSP decomposition followed by NSDFB

Several image enhancement algorithms increase noise when amplify weak edges. Both noise and weak edges produce low-magnitude coefficients but weak edges have geometric nature and noise does not have geometric nature. So, we have to distinguish them by using NSCT because NSCT is shift-invariant transform. In this transform, each pixel of sub-band correspond to original image in the same spatial location. It is necessary to collect geometrical information from pixel by pixel through NSCT coefficient. There are three kinds of pixels in this transform such as strong edges, weak edges and noise. First, the strong edges correspond to those pixels with large magnitude coefficients in all sub-bands. Second, the weak edges correspond to those pixels with large magnitude coefficients in some directional sub-bands but small magnitude coefficients in other directional sub-bands within the same scale. Finally, the noise corresponds to those pixels with small magnitude coefficients in all sub-bands. Based on this observation, we can classify pixels into three categories by analyzing the distribution of their coefficients in different sub-bands. One easy way is to compute the mean and the maximum magnitude of the coefficients for each pixel across directional sub-bands, and then classify it by

$$\begin{cases} \text{Strong edges}, & \text{if mean} \geq c\sigma \\ \text{Weak edges}, & \text{if mean} < c\sigma, \max \geq c\sigma \\ \text{noise}, & \text{ifmean} < c\sigma, \max < c\sigma \end{cases} \tag{5}$$

where, c is a parameter ranging from 1 to 5 and σ is the noise standard deviation of the sub-bands at a specific pyramidal level.

The main aim of proposed method is to amplify weak edges and to suppress noise. We have to modify the NSCT coefficients according to the category of each pixel.

$$y(x) = \begin{cases} x, & \text{strong edges pixels} \\ \max\left(\left(\frac{c\sigma}{|x|}\right), 1\right)x, & \text{weak edges pixels} \\ 0, & \text{noise} \end{cases} \tag{6}$$

where, the input x is the original coefficient, and $0 < p < 1$ is the amplifying gain. This function keeps the coefficients of strong edges, amplifies the coefficients of weak edges, and zeros the noise coefficients.

Pseudo code

Step 1: Read mammogram image

Step 2: Extract ROI (256 × 256)

Step 3: Decompose an image into N (N = 4) Levels

Step 4: Calculate the σ of the sub-bands.

Step 5: For each level

a) Calculate noise variance [13, 14]

b) Classify the pixels using Eq.(5)

c) Modify coefficients using Eq.(6)

Step 6: Reconstruct the image using the inverse NSCT

4. PERFORMANCE MEASURES

The main purpose of the proposed metrics is to evaluate the contrast between the target area of microcalcifications or masses and background (surrounding tissue). In this paper, we use two matrices to measure the performance of the image enhancement. The matrices are given below:

4.1 DISTRIBUTION SEPARATION MEASUREMENT

Distribution Separation Measurement (DSM) measures the degree of contrast between enhanced target and background regions. DSM is defined by,

$$DSM = \left(\left|\mu_E^T - \mu_E^B\right|\right) - \left(\left|\mu_O^T - \mu_O^B\right|\right) \tag{7}$$

where, μ_E^T and μ_E^B is a mean gray level of the target (T) and background (B) area of the enhanced mammogram, μ_O^T and μ_O^B is a gray level of the target (T) and background (B) area of the original mammogram (O).

4.2 TARGET TO BACKGROUND CONTRAST ENHANCEMENT MEASURE

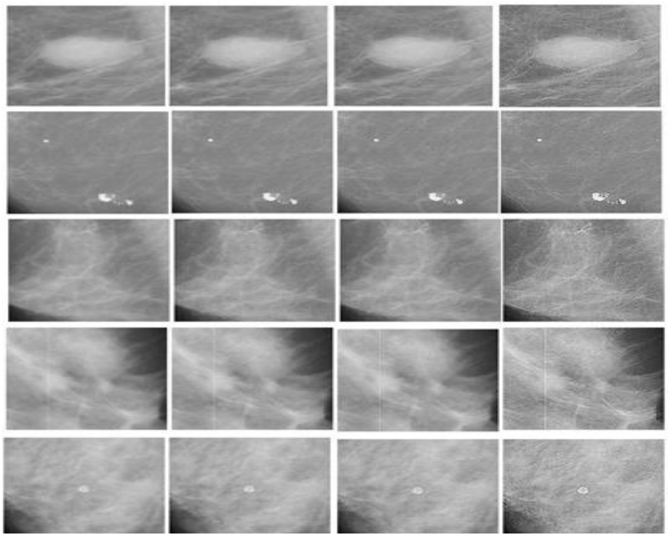
Target to Background Contrast (TBC) enhancement measure is used to evaluate the homogeneity of the microcalcifications or masses and Maximizing the difference between the target and background mean gray levels. It is computed by,

$$TBC = \frac{\mu_E^T \mu_E^B - \mu_O^T \mu_O^B}{\sigma_E / \sigma_B} \qquad (8)$$

where, σ_E and σ_B are the standard deviations of the target region of the enhanced and original mammograms.

5. EXPERIMENTAL RESULTS

This work has been implemented and tested using MATLAB 2013. The test sample database [17] contains 322 digital images. The HAAR 2D DWT can capture only limited directionality information whereas CT can capture multi-scale and directionality information and produce good quality visual content but it may produce unwanted alteration after the modification of coefficient which will affect reconstruction of image and not shift-invariant. The proposed method has completely shift-invariant transform and also compared with HAAR 2-D Discrete Wavelet Transform and Contourlet Transform (CT). The measurement performance is evaluated by Distribution Separation Measurement (DSM) and Target to Background Contrast Enhancement Measure (TBC) which is shown in Table.1 and visual quality of mammogram is also shown in Fig.4.



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

Fig.4. Sample Mammogram Enhancement Images: (a). Extracted ROI, (b). HAAR 2D DWT, (c). CT, (d). NSCT

Table.1. Numerical results using DSM and TBC metric

Extracted ROI	Proposed Method		Contourlet Transform		HAAR 2D DWT	
	DSM	TBC	DSM	TBC	DSM	TBC
mdb025	9.3421	0.0439	7.4737	0.0306	6.0723	0.0202
mdb075	14.8485	0.0691	11.8788	0.0551	9.9484	0.0481
mdb220	11.9047	0.0596	9.7619	0.0452	8.3332	0.0392
mdb213	15.4231	0.0721	12.6469	0.0608	9.2538	0.0411
mdb227	8.221	0.0371	6.8234	0.0251	4.9326	0.0153

6. CONCLUSION

In this paper, we have proposed completely shift-invariant NonSubsampled Contourlet Transform for efficient mammogram enhancement. This transform provides perfect reconstruction after modifying coefficient, faster implementation and also clearly distinguishes noise edges and weak edges. The implementation shows better visual quality mammogram image and numerical result than Haar 2D DWT and Contourlet Transform.

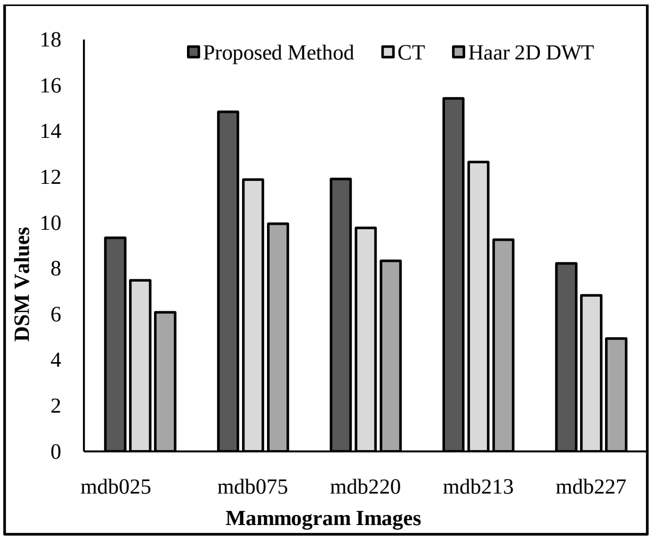


Fig.5. DSM Matric Plot

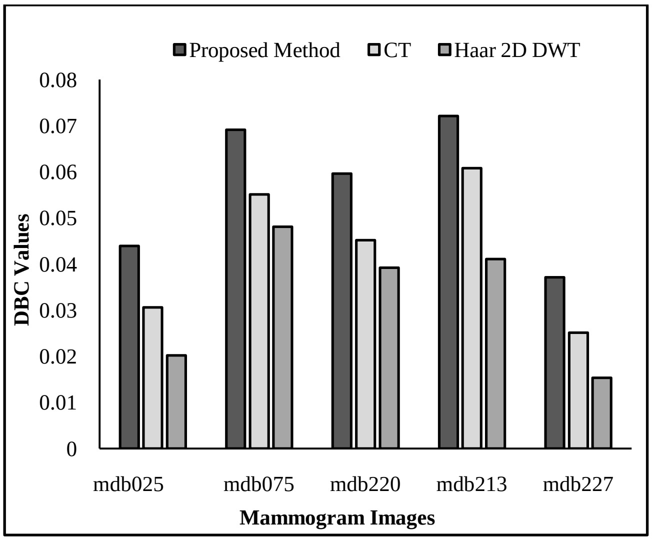


Fig.6. TBC Metric Plot

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