# A Novel Image Processing Algorithm Based On Pixel Approximation for Accurate Breast Cancer Identification and Segmentation

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**Abstract**

Image processing is widely accepted in the field of medical image processing for improvement in image for detection of disease in earlier stage. Image processing with respect to time factor provides appropriate detection of tumors in different cancer detection. In cancer detection process important factors considered are accuracy and quality of the image with minimal processing time. This requirement leads to the challenge of image processing technique with effective mechanism. In this research proposed a IBCR-SBI (Intensity based Cramer Rao - Straighten Boundary Condition) mechanism for improving processing time and accuracy for breast cancer. To improve the accurate detection of tumor extraction is adopted Cramer-Rao mechanism based on the intensity of the pixel. For the further efficiency improvisation of breast cancer detection straighten boundary (SBI) approach is adopted for cancer edge detection. In final stage for the extracted part through SBI and Cramer-rao approach histogram equalization is adopted. Simulation results reveals that proposed approach effectively segmented and extracted cancer in breast.

***Keywords:*** Cramer – Rao, Straighten Boundary Condition, Image extraction, Segmentation, IBCR-SBI

## Introduction

Cancer is solely associate abnormal growth of cells and body cells divide during a continuous manner and invade to encompassing tissues (Vidya, V. K., & Mathew, S., 2016). Cancer is usually classified as benign and malignant plenty in this benign ones square measure straightforward cysts that does not advance of near tissues which implies that it not cancerous in nature. Whereas malignant plenty unfold to different elements of the body and grow in different organs and bones. Carcinoma that starts as a breast lump is that the leading cancer diagnosed among ladies. Within the western countries the surveys shows that one out of eleven ladies is tormented by carcinoma at some stages in their life. Most of the days carcinoma does not exhibit any symptoms within the initial stages. In later stages it are often modification within the breast form, dimpling of the skin, fluid returning from the mamilla, or a red scaly patch of skin. the first detection and timely medical treatment square measure the sole factors liable for the long run survival of carcinoma patients. X ray diagnostic technique is taken into account because the golden normal tool for carcinoma detection. however it's possessed with high false negative and positive rate. it's not applicable within the case of ladies with dense breast tissue (Huynh, P. T et al., 1998). Applied mathematics model of texture contemplate mammographic look as a spatially variable structure. it's not wide used since the synthesis speed is extremely low during this technique (Rose, C. J., & Taylor, C. J., 2003).

Mammogram is associate economical technique sure enough high risk cases. however the lesion sensitivity and specificity determines the accuracy of this technique (Brockway, J et al., 2004). Microwave imaging is amid a major quantity of scatter that falsifies the image (Abbosh, Y. M., 2014). Electrical electric resistance imaging is related to high price (Campisi, M. S et al., 2014). radical Sound square measure usually aforesaid to be advanced owing to information decomposition, it are often delineate in terms of speckle data. radical sound imaging technique utilizes high frequency sound waves to explore inner elements of the bod without damaging and noninvasive technology. This technology implies that it will not alter the target being tested and without any pain or discomfort. Radical sound waves square measure emitted from a transmitter to the article which can mirror back if there's associate impurity or a crack. The resultant echoes square measure analyzed to extract completely different parameters. High detection resolution, low price and high flexibility square measure the opposite blessings of radical sound imaging. Ultrasound imaging (UT) has well-tried effective for softtissue characterization. It uses laptop power-assisted style for classification. Lesion segmentation plays an important role within the CAD system since the computation of options associated with lesion form is essentially addicted to the accuracy of segmentations (Tan, T et al., 2012). Radial Gradient Index (RGI) filtering technique is employed to sight lesions on breast ultrasound pictures mechanically. during this technique pictures square measure sub-sampled by an element of four. The overlap between lesions reduces the accuracy of this technique. Watershed segmentation are often used for initial lesion detection. however the Region of Interest obtained through this technique isn't correct that falsifies the any processes (Hoon, M., & Yap, M ., 2008). Edge detection is utilized to outline Region of Interest during a explicit technique. however the potency of this technique is way relied on the kind of edge detection rule used machine-controlled breast Ultrasound mistreatment adaptative threshold is employed for multi-dimensional growth detection. the potency of this technique depends upon the edge selected (Vidya, V. K., & Mathew, S ., 2016).Feed forward back propagation neural network is another technique wont to classify benign and malignant breast growth. Here Levenberg-Marquardt (LM) is employed because the coaching rule. The accuracy of this method is outlined because the magnitude relation of varies quantity of samples properly classified to the whole number of samples tested (Su, Y et al., 2011).

In this paper, proposed a IBCR-SBI scheme for efficient detection of breast cancer with minimal processing time. The proposed scheme utilizes cramer-rao mechanism for calculating intensity of the pixel in image. Pre-processed image is applied with Cramer- Rao scheme to detect the higher intensity pixel with cancer part. Segmentation of cancer part using Cramer-Rao contains other normal tissues and other parts hence SBI is applied to remove unwanted parts. Through the application of SBI cancer part alone highlighted and extracted with minimal processing time. Results of the proposed approach reveals that proposed IBCR-SBI scheme detect the cancer with higher accuracy with minimal processing time.

## Related Works

The existing analysis work administered within the cancer image process application square measure reviewed (Kusakunniran, W et al., 2016) projected a needs 2 main steps which can be targeted during this paper. they're the standard assessment and therefore the segmentation of diabetic retinopathy pictures. within the image quality assessment, four options (namely color, contrast, focus, and illumination) are investigated. As a result, the distinction bar chart within the Principal element Analysis (PCA) area is employed. within the image segmentation, the bar chart leveling is employed within the pre-processing. Then, the image segmentation supported the reiterative choice and therefore the grabcut rule is applied. The experimental results demonstrate that the projected technique can do terribly promising performance. Wen, H et al., 2016 developed a picture improvement rule that supported moving ridge domain homomorphic filtering and distinction restricted adaptational bar chart leveling (CLAHE). Firstly, the image is rotten by moving ridge transformation, the image is rotten into low-frequency and high-frequency coefficients of first layer of moving ridge domain. Then the low frequency coefficients square measure processed by associate degree improved homomorphic filter, and so linear amplified. The high frequency coefficients square measure processed by moving ridge threshold shrinkage, and so the moving ridge reconstruction is performed. Finally, the distinction restricted adaptational bar chart leveling (CLAHE) is employed to change the image's bar chart, and therefore the process of the image is completed. The quality of image enhancement is carried on the subjective and objective evaluation, and compared with some other enhancement algorithms. Experimental results show that the algorithm can effectively enhance the texture detail of medical X-ray images, increasing the brightness and contrast, suppress noise, better than the general traditional enhancement algorithms. Shajy, L et al., 2014 evaluated the conventional HE enhancement process outputted an excessive contrast result. Which leads to poor classification result, especially in medical image processing. In this paper we discussed about various HE methods for the enhancement of sputum cytology images. Our ultimate aim is, to develop an efficient algorithm to detect lung cancer at early stage. The challenging problem, we faced, in this work is to find out a proper algorithm for the enhancement of sputum cytology images. Here we consider some famous HE algorithm for the enhancement of sputum cytology images. The Recursive Mean Separate Histogram Equalization Method (RMSHE) gives result in sputum cytology image enhancement. Huang, L et al., 2013 performed Histogram equalization is a significant application for image gray level transformation, which is widely used in image enhancement processing. We adopt keeping encrypted histogram-equalized image data in the database as the security strategy for our personal healthcare information cloud platform system. Three kinds of symmetric encryption algorithms are used to test histogram equalized image. The experiment results show AES encoding rule appropriate for our personal care data system. Esener et al., 2015 aimed to style a laptop power-assisted identification system for carcinoma identification and a mamogram dataset ready throughout the Image Retrieval in Medical Applications (IRMA) project is employed for the verification of the system. In accordance with this purpose, feature extraction is accomplished mistreatment native Configuration Pattern rule on the preprocessed mamogram pictures by bar chart leveling followed by Non-Local suggests that Filtering. additionally to those options, vector area is extended by some applied mathematics and frequency-domain options. Besides, feature choice is performed by applying consecutive Forward Feature choice (SFS) rule on the obtained options. Finally, designated options square measure classified in an exceedingly 2-stage theme into three completely different classes (normal, benign, malignant) mistreatment linear discriminant classifier, Fisher's linear discriminant analysis, supply linear classifier, k-nearest neighbor classifier, Naïve Bayes and call tree classifiers. The results earned at the cases, within which feature choice is performed and not, square measure compared and it's ended with about eighty eight the most success rate is accomplished in each cases.

**Methodology**

The aim of this research to effectively perform the medical image processing for cancer application. As per the review of existing report it is identified that cancer disease is severe threat to human begins life. Hence in this research concentrate on examining and analyzing cancer disease image processing especially breast cancer. In breast cancer detection images are occurred from mammogram and undergo processing. The data for the breast image processing are collected and processed using proposed approach. In figure 1 overview flowchart of the proposed approach is presented. In the primary stage of the image processing image data are collected by use of mammogram image acquisition method which is followed by conventional image enhancement approach.

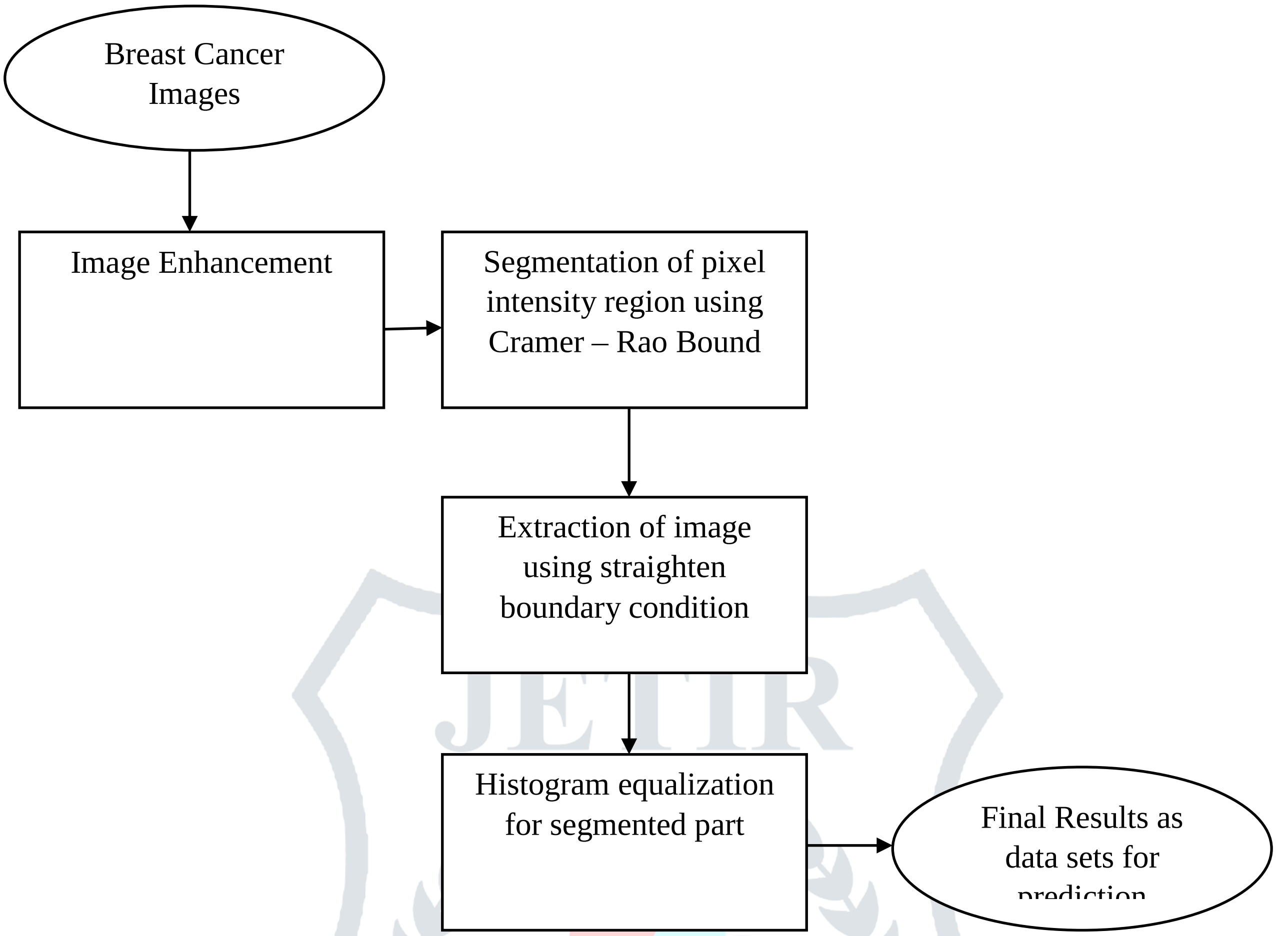


**Figure 1. Proposed Architecture**

In the next stage of the image processing to improve the performance of the cancer detection based on the intensity. The intensity values in the images is used for cancer detection based on the Cramer – Rao method based on upper bound and lower bound condition. Based on this intensity pixels within the lower bound range of pixel with higher pixel intensity to lower intensity. After the identification of pixel intensity with the specified range the cancer affected part need to be segmented for increasing the processing time and cancer detection efficiency. Since the main objective of this research is to improve the brest cancer detection accuracy for the segmented part based on straighten boundary condition cancer affected image is histogram equalized and final dataset were created. In Cramer-Rao approach through the mathematical formulation intensity of the pixel will identified and provided the value of the cancer affected pixel intensity for extraction of cancer affected region. Through the extraction of intensity pixel by cramer-rao rule image part are segmented using SBI condition. From the segmented part images affected with cancer in mammogram images can be identified effectively with minimal time. The image intensity pixel with cancer are stored in a separate datasets for future processing.

***Steps for IBCR-SBI***

1. Start
2. Acquire Breast Image through Mammogram image
3. Pre-processing of breast image
4. Evaluating the intensity of breast cancer image
    a) Pixel intensity below 11 are normal tissues
    b) Pixel intensity equal to or nearer to 38 are cancer cells

5. Segmentation of higher pixel intensity part from breast image

6. Extraction of cancer part alone using SBI approach

**Calculation of CRB (Cramer- Rao Bound)**

A classical problem in statistical signal processing consists of recovering a signal $x$ from a vector of $Q$ observations

$$y = x + w$$

where $w$ is a noise vector. Here, we assume that $w \in \mathbb{C}^Q$ is a realization of a circular Gaussian random noise vector $W$ with zero-mean and covariance matrix $\Gamma = \mathrm{E}[WW^H] \in \mathbb{C}^{Q\times Q}$ ($(\cdot)^H$ denotes the transconjugate operation). We assume that the signal $x \in \mathbb{C}^Q$ admits a sparse representation in a finite dictionary $\mathcal{E} = \{e_\upsilon \mid \upsilon \in \mathbb{R}\}$ of vectors of $\mathbb{C}^Q$ which are parameterized by a scalar variable $\upsilon \in \mathbb{R}$. More precisely, there exist $M \in \mathbb{N}*$, $c = [c1,...,] \top \in (\mathbb{C}*)M$ and $\nu = [\nu1,...,\nu M] \top \in \mathbb{R}M$ such that

$$x = \sum_{n=1}^{M} c_n e_{\nu n} = [e_{\nu 1} \ldots ] = Ec$$

The vector $y \in \mathbb{C}^Q$ is thus a realization of a random vector $Y$ with probability density function

$$\mathrm{p}Y\,|_{c,\nu}(y) = (1/\,(\pi)^M(\,\det(\Gamma))^{1/2}\,)*\exp\,(\,-(y-Ec)\,^H\Gamma^{-1}(y-Ec)\,)$$

In the following, it is assumed that $\upsilon \rightarrow e\upsilon$ is a twice differentiable function.

***Calculation of the CRB***

Up to an additive constant, the negative-log-likelihood is equal to

$$\mathcal{L}(y \mid c, \nu) = w^H\Gamma^{-1}w$$

In the following $w_R$ and $w_I$ denote the real part and the imaginary part of $w$, a similar notation being used for other complex-valued vectors and matrices.

Let us first look at the expression of the Wirtinger's derivative [7] of the neg-log-likelihood with respect to the conjugate of $c$:

$$\partial\mathcal{L}(y \mid c, \nu)\,/\partial c^* = 1\,/2\,((\partial\mathcal{L}(y \mid c, \nu)\,/\partial c_R + \imath\,\partial\mathcal{L}(y \mid c, \nu)\,\partial c_I\,)) = -EH\Gamma^{-1}w$$

We have then

$$(\partial^2\mathcal{L}(y \mid c, \nu)/\,\partial c_R\partial c^\top{}_R\,) = -2\,\partial\,(\,{}^\top{}_R\,(\Gamma^{-1}E)_R + w^\top{}_I\,(\Gamma^{-1}E)_I\,)\,\partial_{cR}$$

$$= 2\,\mathrm{Re}\{E^H\Gamma^{-1}E\}$$

and, by similar calculations,

$$(\partial^2\mathcal{L}(y \mid c, \nu)/\,\partial c_R\partial c^\top{}_I\,) = -2\,\mathrm{Im}\{E^H\Gamma^{-1}E\}$$

$$(\partial^2\mathcal{L}(y \mid c, \nu)/\,\partial c_I\partial c^\top{}_I\,) = 2\,\mathrm{Re}\{E^H\Gamma^{-1}E\}$$

On the other hand, the neg-log-likelihood can be re-expressed as

$$\mathcal{L}(y \mid c, \nu) = (\,y - \sum_{n=1}^{M} c_n e_{\nu n}\,)H\,\Gamma^{-1}\,(\,y - \sum_{n=1}^{M} c_n e_{\nu n}\,)$$

For every $n \in \{1,...,\}$, this leads to

$$(\partial\mathcal{L}(y \mid c, \nu)\,\partial_{\nu n}) = -2\,\mathrm{Re}\{c^*{}_n(e'{}_{\nu n}\,)\,^H\Gamma^{-1}w\}$$

where $e'\,\nu n$ is the gradient of $\upsilon \to e_\upsilon$ at $\nu_n$.

For the second-order derivatives, we deduce that, for every $(n, m) \in \{1,...,\}^2$,

$$(\partial^2\mathcal{L}(y \mid c, \nu)\,/\partial\nu_n\partial\nu_m = 2(\,\mathrm{Re}\{c*_n c_m(e'_{\nu n})^H\Gamma^{-1}e'_{\nu m}\} - \mathrm{Re}\{c*_n(e''_{\nu n})^H\Gamma^{-1}w\}\delta_{n-m})$$

$$(\partial^2\mathcal{L}(y \mid c, \nu)\,/\partial\nu_n\partial c*_m = 1/\,2\,(\partial^2\mathcal{L}(y \mid c, \nu)\,/\partial\nu_n\partial c_{R,m} + \iota\,\partial^2\mathcal{L}(y \mid c, \nu)\,\partial\nu_n\partial c_{I,m})$$

$$= c_n e^H{}_{\nu m}\Gamma^{-1}e'_{\nu n} - (e'\quad)^H\Gamma^{-1}w\,\delta_{n-m}$$

$\mathcal{F}_p = \mathrm{E}\,[\partial^2\mathcal{L}(Y \mid c, \nu)\,/\partial_p\partial_p{}^\top\,] \in \mathbb{R}^{3M\times 3M}$.

Since $W$ is zero-mean, which yield, for every $(n, m) \in \{1,...,\}^2$,

### Histogram Equalization

Histogram equalization is a process of flattening the histogram, where the distribution of the value of the degrees of gray in an image made flat. To be able to perform a histogram equalization is necessary which the cumulative distribution function of the cumulative histogram is. Histogram equalization is used to improve the quality of segmentation. Excessive segmentation is a major problem facing the segmentation using watershed algorithm because it needed a good preprocessing to avoid excessive segmentation. Value histogram equalization results are as follows (Radhiyah, A et al., 2016):

$$w = \frac{c_w.t_h}{f_{lx}\cdot f_{ly}}$$

Where, $w$ - value of gray histogram results

$c_w$ - Cumulative histogram of w

$t_h$ - Threshold degrees of gray

$f_{lx}\cdot f_{ly}$ - Image size

### Histogram Equalization in Image Processing

In the past, multiple contrast enhancement techniques were developed for image visualization. We can categorize them into two groups mainly, the spatial domain- based technique and the transformation- based technique. Spatial domain are implemented directly with the image pixels (Mundhada, S. O., & Shandilya, V. K., 2012). Some of the examples are the basic histogram equalization (HE) and the modified HE which can be further categorized into the global histogram equalization (GHE) and local HE- based methods (Koh, N. C. Y et al., 2016; Lidong, H et al., 2015). In the basic HE technique, HE initially computes the probability distribution function (PDF) from the image histogram. The cumulative distribution function (CDF) is calculated and then plug in to the transfer function of an image. Next, the new distribution of gray level is remapped based on the respective CDF. The probability of occurrence of a pixel of level k in the image is:

$$P_x(k) = \frac{n_k}{n}$$

Where $n_k$ is the number of pixels at level $k$ and $n$ is the sum number of pixels in the image. The formula of CDF of the image is:

$$cdfx(k) = \sum_{j=0}^{t} P_x(k)$$

Applying the transformation function:

$$TF = (cdfx(k))(x_{\max} - x_{\min}) + x_{\min}$$

Where $x_{\max}$ is the maximum gray level and $x_{\min}$ is the minimum gray level of the output image. The HE stretches the high probability levels better than low probability levels and therefore allowing areas of lower local contrast such as the brain lesion to gain a better contrast. However, HE constantly distributes the output histogram using a cumulated histogram to produce an overly enhanced image.

To overcome the problem, the GHE modified technique such as the extreme level eliminating histogram equalization (ELEHE) proposed by Tan et al., and adaptive gamma correction with weighting distribution (AGCWD) proposed by Shih et al., was introduced. The ELEHE technique eliminates the two extreme grayscale levels, 0 and 255 while normalizing the resultant distribution and finally maps the transfer function on the image (Tan, T. L et al., 2012). In AGCWD technique, the authors brightens the image using the gamma correction and the probability distribution of luminance pixels (Huang, S. C et al., 2013). The ELEHE produces a darken lesion area but also darkens the other tissue areas making it difficult to detect the brain lesion while the AGCWD brightens the image but brain image details are loss. On the contrary, the LHE technique such as the contrast limited adaptive histogram equalization (CLAHE) (Pizer, S. M et al., 1987) proposed by Pizer et al., and extreme level adaptive eliminating histogram equalization (ELEAHE) (Tan, T. L et al., 2012) by Tan et al., was developed to overcome the shortcomings of the GHE technique. CLAHE is designed to suppress noise and unwanted over enhancement in an image. CLAHE is done by separating the original image into non- overlap sub- blocks while enhancing each subblocks solely and recombines the sub-block image using bilinear interpolation. In ELEAHE, the image is separated into sub- blocks. The extreme levels of the sub- block image are eliminated before performing redistribution of pixels and the image blocking effects are reduced using the bilinear interpolation. Enhancing the noise in the image is the drawback of both techniques (ELEAHE and CLAHE). The other group of contrast enhancement technique is the transformation or frequency domain technique which decomposes the image into the frequency domain such as the discrete wavelet transform (DWT), Fourier transform (FT) and discrete Fourier transform (DFT).

**Mathematical Formulation**

Image data along the boundary of target structure are extracted and transformed to a rectangular image space where the target boundary is roughly straightened. Resampling the input image along the non-uniform direction was also applied in this process creates an optimal region of interest in which features are mostly oriented in a single direction. A curvilinear prior shape of a model corresponding to the boundary of target structure is used. Then the normal vector which is perpendicular to the prior shape at each point is calculated. The straightened region is then extracted along the normal vectors and transformed into a rectangular boundary image. This simplifies segmentation by optimizing the edge detection in a single direction.

***Transformation of input image to SBI***

In this section, we review the SBI creation and propose a new modification for MATLAB implementation of the method. As stated the SBI is created by a coordinate transformation along a prior shape (PS) from the input image. The PS data is a set of n positive integer pairs showing the coordinates of the PS by the curve C defined as follows:

$$C = \{\bigcup P_i\ x_i, y_i\ , i = 1, \ldots, n\}$$

For each point of Pi, a corresponding normal vector Ni, which is perpendicular to the PS at each point, is calculated by

$$N_i = N_{xi}, N_{yi}$$

The SBI is created by a transformation from the input image along the PS defined as follows:

$$T_m\ x_i, y_i = (N_x \cdot A_v + xi, Ny \cdot A_v + y_i)$$

where $A_v$ is an acquisition vector that determines the number of samples corresponding to each normal vector. Finally, the transformation Tm is applied in the input image I along the curve C to create the SBI as follows:

$$SBI = I \cdot T_m(x_i, y_j), x_i, y_j \in C$$

**Redundant and low-resolution data in SBI**

As mentioned previously, the SBI is constructed by a transformation in which the normal vector multiplied by an acquisition vector points to the sampling points in the input image. Pixels along a normal vector, which is perpendicular to the PS, are sampled from the original image to create one line of the SBI corresponding to each pixel of the PS. There are some challenging issues in construction of the SBI that are discussed here. The first problem arises when the slope of the PS changes rapidly. As shown, the slope of the PS around the greater changes rapidly. In this situation, normal vectors converge towards the inside of the object and intersect. This causes that a pixel in this area be sampled by different normal vectors and appears in the SBI in multiple places. If the edges of the object are close to the PS this issue does not cause any problem. However, in the experiments with clinical data, it cannot be guaranteed that the PS is initialised very near the targeted structure. Fig. 2b shows that the PS is a little far from the boundary of the femoral head around the greater trochanter and that its normal vectors intersect causing multiple samples of the edges data. Indeed, the order of edges data can be appeared in the SBI incorrectly. This problem is shown in Fig. 2 where the edge samples d1 and d2 corresponding to the normal vectors at points P1 and P2 are appeared in the SBI in an opposite order to the PS points. The experimental results in these situations show jagged edges and circulation artefact in the final segmentation results shown in Fig. 2.

When the SBI is constructed, the edge data is extracted by the minimal path algorithm. Then the edge coordinates from the SBI are translated to the coordinates of the original image by a reverse transformation. Here we propose an algorithm that checks the edge data from the SBI and removes the redundant data which creates artefacts. The proposed algorithm checks validity of the edge data at each line of the SBI and in case of redundancy disqualifies it for reverse transformation. The reverse transformation is applied only on valid and qualified data. The detail of the algorithm is as following.

The performance of proposed Cramer- Rao based SBI approach for segmentation and extraction of cancer from mammogram is discussed in this part. Assume that the edge data up to point P in was transformed from the SBI to the input image and $n_1$ is the normal vector at pixel p. This area is depicted in light blue along the PS up to point p and $n_2$ is the normal vector at q which is the next pixel in the PS. d is the edge data corresponding to $n_2$ and we will now examine its validity as edge data. The normal vectors n1 and $n_2$ intersect at point x. If the coordination of d resides in the area, which has already been transformed (blue area), it is considered redundant data and is not transformed to the original image. In the image d is located in the blue area and the algorithm does not transform this data to the input image and proceed to check data correspond to the next normal vector. In this case, the next normal vector is compared with the normal vector corresponding to the last transformed edge data. If the edge is found on the left side of x (in this figure) the data is valid and transformed to the original image. If $n_2$ is parallel to $n_1$ or if their intersection point is outside of the blue area the edge data corresponding to $n_2$ would also qualify.

As opposed to the previous problem of the redundant data, the second problem occurs on the other side of the PS where data is sampled from scattered normal vectors. If an edge is far from the PS and located on a side of the PS where normal vectors diverge, the edge data is sampled with a very low resolution. The image shows that normal vectors around the corner of the femoral part of tumor in which the slope of the PS is changed rapidly and the angle between every two consecutive normal vector is significant. In this situation some parts of the image located between normal vectors are not sampled. The large change of the slope of the PS causes the low resolution of sampling data around the edge increasing the chances of wrong edge detection.

**Simulation Results Analysis**

In this research to evaluate the performance of the proposed approach histogram processing of images are evaluated. The images collected from mammogram are evaluated through simulation in MATLAB. Input images are processed using enhanced approach and intensity values are evaluated using cramer-rao approach. By the use of SBI the images are straighten and edge values are identified. The image processing adopted in this research for processing are presented and elaborated in this section.

| Parameters | Values |
|---|---|
| Minimal Pixel Intensity | 11 |
| Minimal Cramer Limit | 315.039680040467 |
| Minimal Distance | 315.039680040467 |
| Maximal Pixel Intensity | 38 |

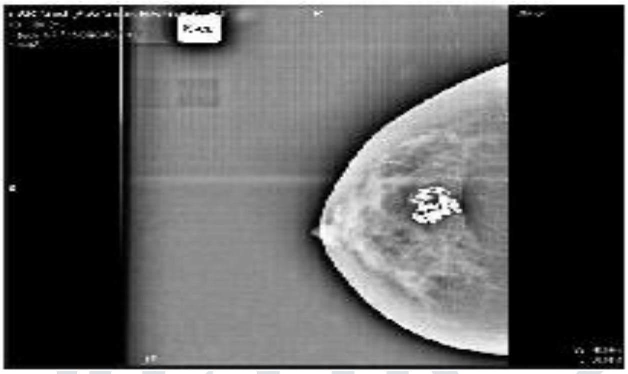

**Figure 3: Pre processed Image**

The figure 3 illustrates the image preprocessed for processing image with SBI and Cramer-Rao limit conditions. For the processed image the image get smoothened and processed accordingly. Comparison of original image with processed image illustrate that our preprocessing mechanism effectively smoothen mammogram images. This pre-processed image is applied as input for Cramer-Rao mechanism with varying pixel intensity value. Based on image pixel intensity different points of image are extracted and segmented for clear dataset identification process. Cramer-rao approach evaluate the input pixel based on intensity of the image pixels. To obtain the reference segmentation for comparison with the automatically obtained results from the Cramer-Rao, the mammogram images were peer reviewed lab for analysis. From that meeting, expert general consensus on the tumour outline on 2D (axial) slices of patients, which is considered as a gold standard in current clinical practice was obtained. In order to analyse inter-variability in manual segmentation,two independent radiation separately in breast. For intra-variability evaluation both RO1 and RO2 repeated this procedure on the same dataset approximately for analysis. The proposed technique is evaluated based on the analysis of efficient detection of cancer in human beings. Generally, the mammogram results were also compared to breast outlines. In case of, PLCSF performance assessment, two metrics were utilized; Spatial overlap between two segmentation results was measured using DSC. A high value of Digital Still Camera (DSC) (i.e. 1) indicates good agreement between two segmentation results. Compared to original pixel distance, Modified Hausdorff Distance (MHD) reduces impact of outliers and noise and it was used for shape variation evaluation between segmentation. In order to facilitate this process this proposed approach concentrate on detection and segmentation of cancer part with minimal amount of time for processing. The figure 4 illustrated the image segmented and extracted using proposed IBCR-SBI scheme. Before applying the proposed scheme as said in methodology part pre-processing is performed.

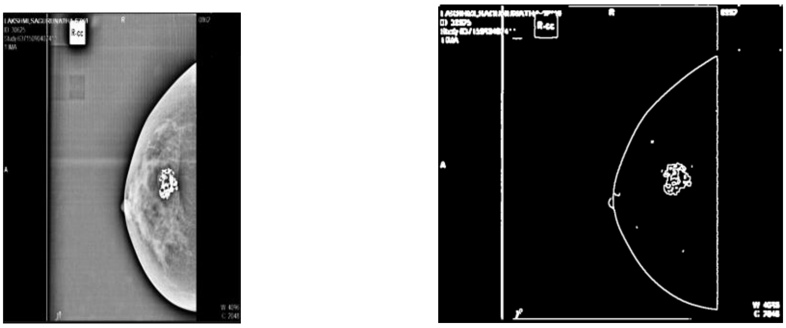

**Figure 4: Tumor Segmented and Extracted**

The proposed technique efficiently detect the cancerous part and facilitate the doctor or specialist to detect cancer effectively. In extracted region clearly cancer part alone identified and other tissues also detected which has high pixel intensity but they are tiny and less in numbers which means it will not affect the performance hence proposed IBCR-SBI scheme works based on intensity of pixels. Generally in existing researches it is stated that segmentation of breast cancer regions is particularly difficult due to the presence of mammogram artefacts, enhancements of other non-cancer regions geometric variability and weak edges of the cancer regions across the patients. Hence in order to resolve this issues in this research cramer-rao based SBI framework was presented in this paper for this task that does not require any manual intervention or training data for the proposed scheme IBCR-SBI. This framework makes no assumption about the shape or size of the cancer regions, thus can successfully segment the cancer regions with geometric variability. Also, the cases used in this study are representative of everyday clinical challenges. In this framework, a novel adaptive determination of parameter pixel intensity distance allowed the estimation of complex bias field present in mammogram slices used in this work. Detection and segmentation of cancer in breast region is performed through Cramer-Rao approach based technique allowed the knowledge of the approximate cancerous position to be embedded in the system, particularly in MFCM (Multi-Functional Card Machine), thus reducing further processing steps to eliminate healthy tissues from cancer detected clusters that are away from the throat region. Comparison of existing technique with the standard SBI showed that proposed Cramer-Rao approach based SBI achieved better results compared to the standard SBI. The continuity and spatial smoothness of the cancer boundary was ensured by evolving the level set surface on the detected cancer region. Quantitative comparison with the Gold Standard (consensus manual outline) on 102 T1 + Gd mammogram axial slices from 10 patients, the system (PLCSF) shows no significant difference in performance (PCC: 0.89, $p < 0.05$) with the method used in current clinical practice.

In existing research done by Doshi, T et al., 2017 proposed a scheme named as pharynx and larynx cancer segmentation framework PLCSF result exhibits improved performance when compared to other algorithms (MS clustering and Ncut). Existing semi-automatic approach for breast cancer segmentation validated on 16 patients (78 axial slices) demonstrated mean correspondence ratio of 0.83 which is comparable to PLCSF DSC of 0.79. However, the semi-automatic approach in required manual-placing of seed points in the breast tumour region or drawing of close loop outside the tumour from expert and have no results to prove any validation on breast cancer. The limitation of the current framework is over segmentation of cancer region in case of similar characteristics of cancer tissues as compared to surrounding tissues. Hence in presented framework to resolve this SBI is applied while in figure 4 for pre-processed image cramer-rao based intensity detects other nearby tissues. This arises problem while cancer is small in number hence proposed approach uses SBI scheme which detect and extract the part with higher accuracy for detecting cancer in breast region. In figure 5 it is clearly observed that propose IBCR-SBI scheme detect the cancer in the breast region without any other tissues which means it increases detection accuracy.

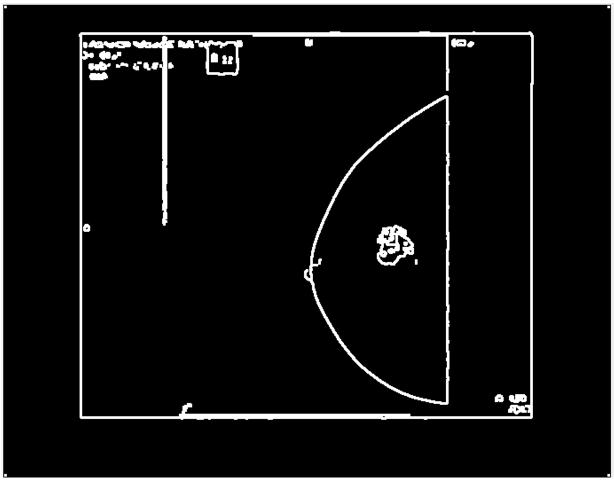

**Figure 5: Image with Straighten Image condition**

One of the main purposes of the automatic cancer region segmentation of T1 + Gd mammogram slices is the reproducibility of the segmentation results that contain intra- and inter- variability from manual segmentation results. For this framework, if the parameters values are unchanged, the system obtains similar results for repeated number of times, indicating the reproducibility of the system. Further, using single modality (T1 + Gd) in RTP can reduce scanning and processing time of mammogram slices and increase the computational efficiency. Thus, this tool can assist RO in RTP to detect and segment breast cancer boundaries from T1 + Gd mammogram axial slices in time-effective and unbiased manner. To the best of our knowledge this is first automatic tool focused on segmentation of BoT and larynx cancer from T1 + Gd mammogram.

| Author | Approximation Time |
|---|---|
| Singh, A. K., & Gupta, B., 2015 | 4.20sec |
| Daniel, E., & Anitha, J., 2015 | 3.87sec |
| Proposed Approach (IBCR-SBI) | 2.87sec |

**Table 1: Comparison of Processing Time**

The system also demonstrated that it can perform robustly against variations caused by different mammogram scanners protocols with different manufacturer and scanner models. In mammogram scanners processing time is considered to be a important parameter hence proposed approach evaluate based on approximation. In table 1 comparison of IBCR-SBI scheme with existing research approach is tabulated. The analysis of approximation time is performed in sec through which proposed IBCR-SBI scheme shows performance with accurate detection of cancer in 2.87sec. Comparison of proposed with other research carried out by Singh, A. K., & Gupta, B., 2015 shows approximation time of 4.20sec and Daniel, E., & Anitha, J., 2015 approach demonstrate approximation time of 3.87sec. Through this it is concluded that proposed IBCR-SBI scheme exhibits minimal approximation time rather than other technique. In overall it is observed that proposed IBCR-SBI scheme shows significant performance in terms of accuracy and processing time which means proposed approach is effective.

## Conclusion and Future Enhancement

An image improvement technique is developing for earlier disease detection and treatment stages; the time factor was taken in account to discover the abnormality issues in target images. Image quality and accuracy is the core factors of this research, image quality assessment as well as enhancement stage where were adopted on low pre-processing techniques based on cramer-rao approach. The proposed technique IBCR-SBI is efficient for segmentation principles to be a region of interest foundation for feature extraction obtaining. The proposed technique gives very promising results comparing with other used techniques. In future based on the collected dataset optimization based approach will be developed for effective detection of cancer affected part.

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