AN OPEN-SOURCE COMPUTER-AIDED DETECTION SOFTWARE FOR NODULES SEGMENTATION USING MAMMOGRAMS.

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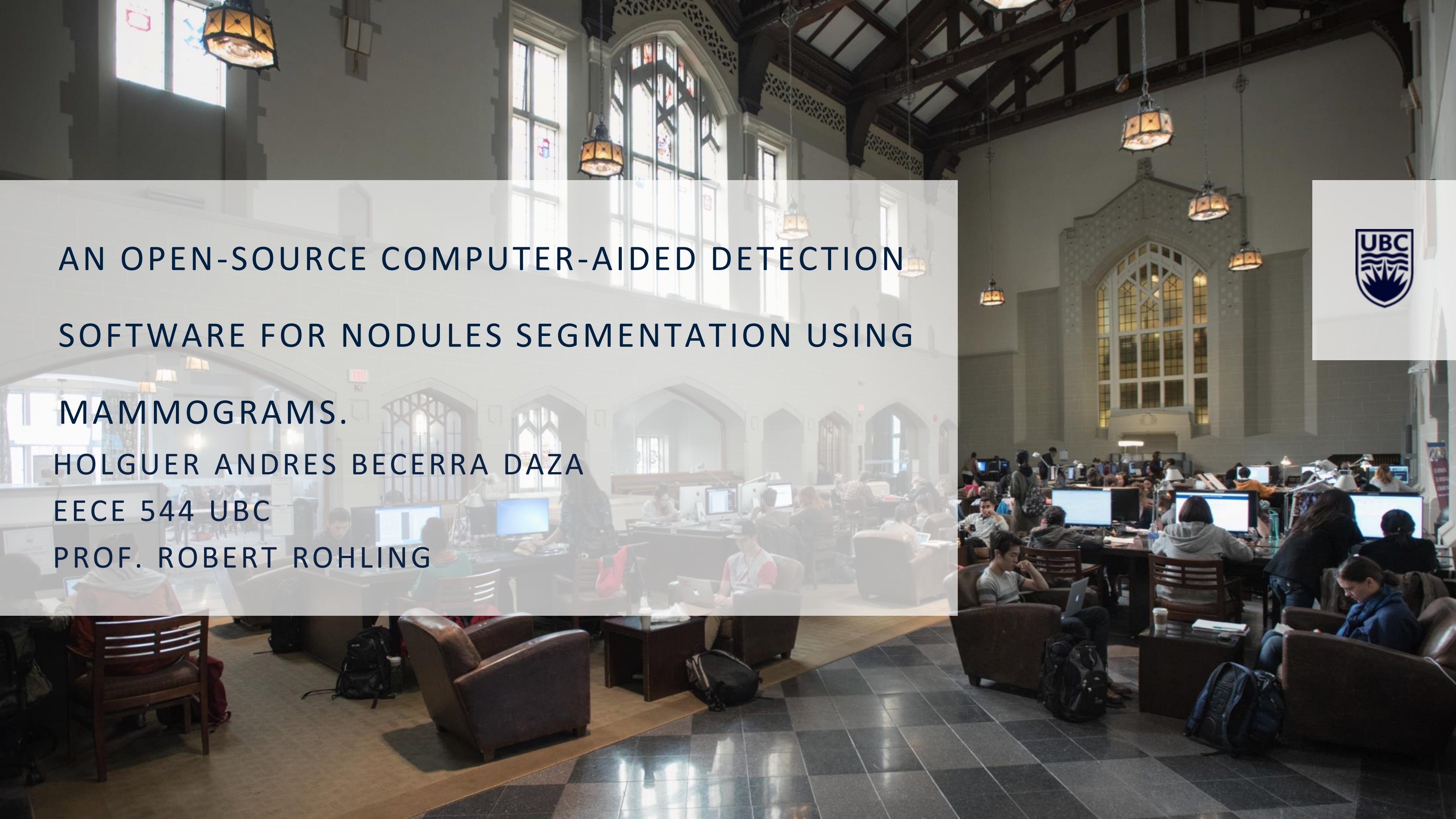


CONTENT

1.INTRODUCTION

MOTIVATION

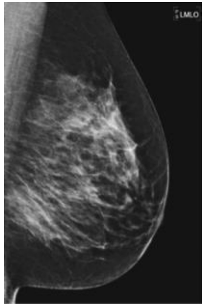
18.000$

Open-source

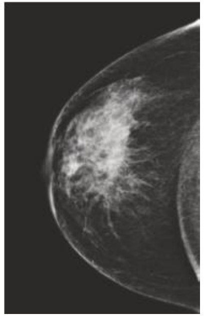
Third world countries

CAD software

clinical interpretation



benign



malign

Medical training as primordial factor

1.1 DATA BASES

http://peipa.essex.ac.uk/info/mias.html

Mini-MIAS database of mammograms

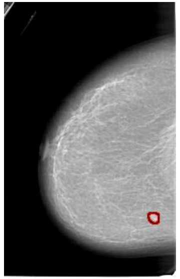
- Regular quality
- Reduced Quality and size of Images

From 2500x4000 to 1024x1024 pixels

http://marathon.csee.usf.edu/Mammography/Database.html

University of South Florida Digital Mammography

- Better quality
- Image classification by radiology assessment



LJPEG 42 microns

1.1DATA BASES

MIAS

- Image format compatibility with regular sw
- Less artifacts and noise
- Smaller image size and depth (8bits)
- Doesn’t have overlays complicating the segmentation accuracy verification process
- Difficult accessibility, lot of forms to sign

DDSM

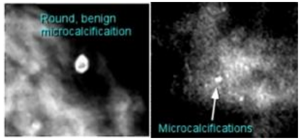
- Better axial resolution and depth 12 bits/pixel
- Specified Overlay and radiology diagnosis assessment specifying the type of view (ML, MLO, CC)
- The images come from several analog screening tests and then digitalized.
- Several artifacts as labels, and noise
- A Non-Standard format so in order to preview the image it is needed a special software.

1.2. BI- RADS BREAST IMAGING REPORTING AND DATA SYSTEM

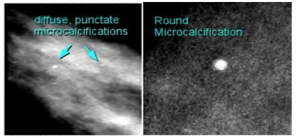
0. Incomplete
1. Negative
2. Benign findings
3. Probably benign
4. Suspicious abnormality
5. Highly suspicious malignancy
6. Known biopsy with proven malignancy

Standardization and reliability

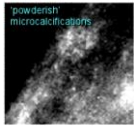
examples

3.


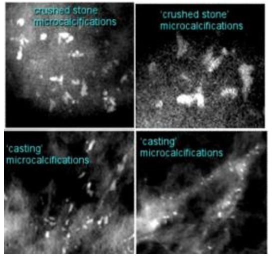
Circumscribed, low density core, architectural changes

4.


Asymmetric, convex, pleomorphic, radio-opaque

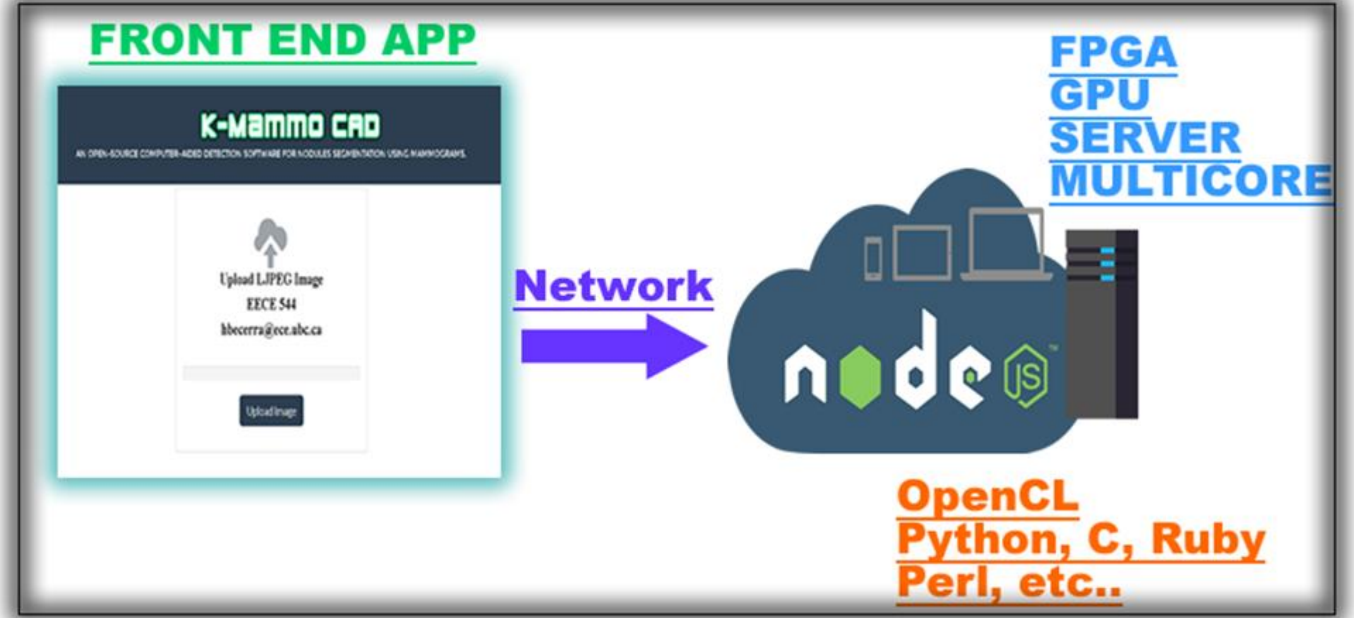
5.


Several pleomorphic micro-calcifications, spiculated and non-circumscribed masses

6.


1.3 SOFTWARE STRUCTURE

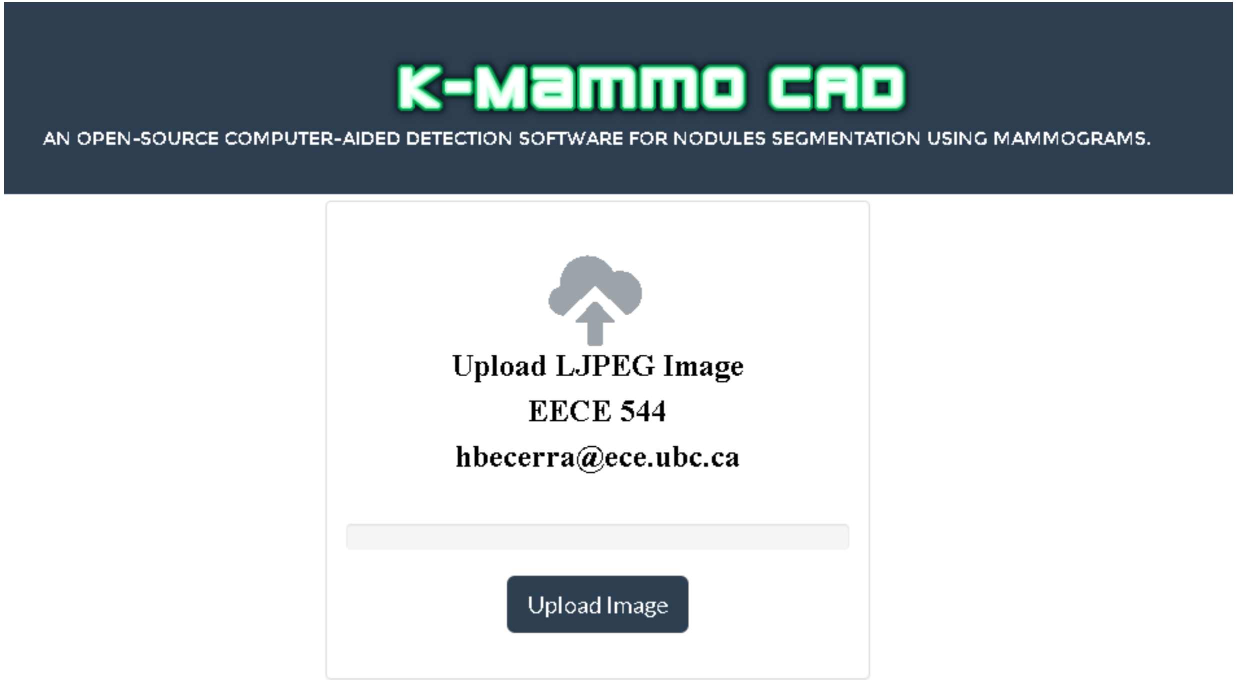
Structure



https://github.com/Adrizcorp/K-MAMM-CAD

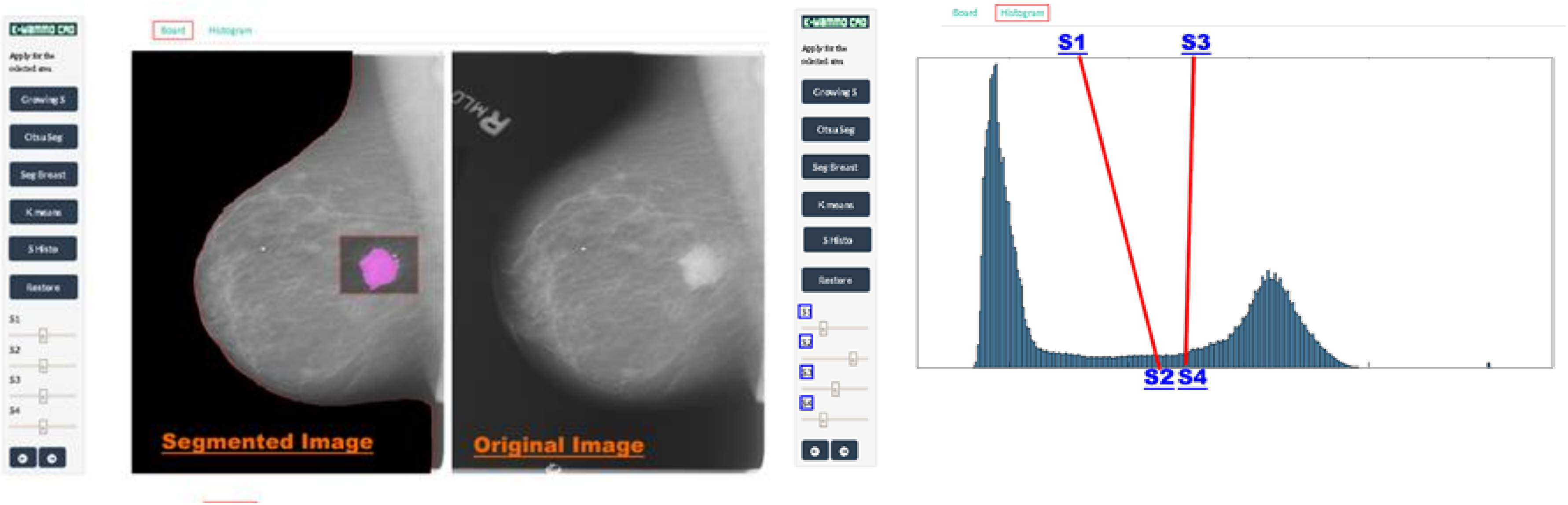
1.3 SOFTWARE STRUCTURE

interface



1.3 SOFTWARE STRUCTURE

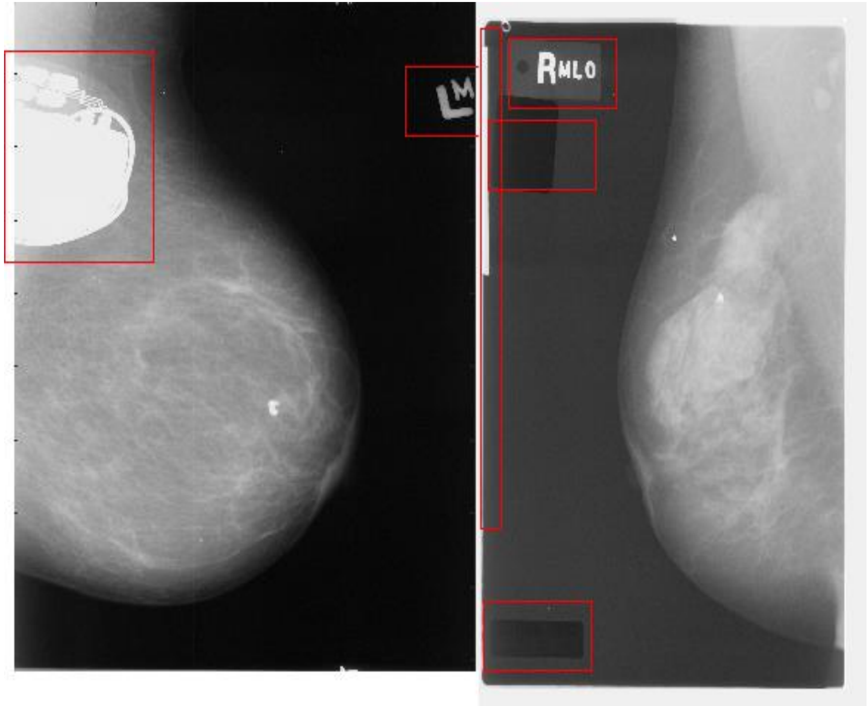
interface



Seed growing segmentation, Otsu Segmentation using thresholding, Breast segmentation in base of Otsu method and sobel edge detection, thresholding segmentation using the histogram of an specific region or the whole image, and K-Means segmentation.

2. TECHNIQUES AND RESULTS

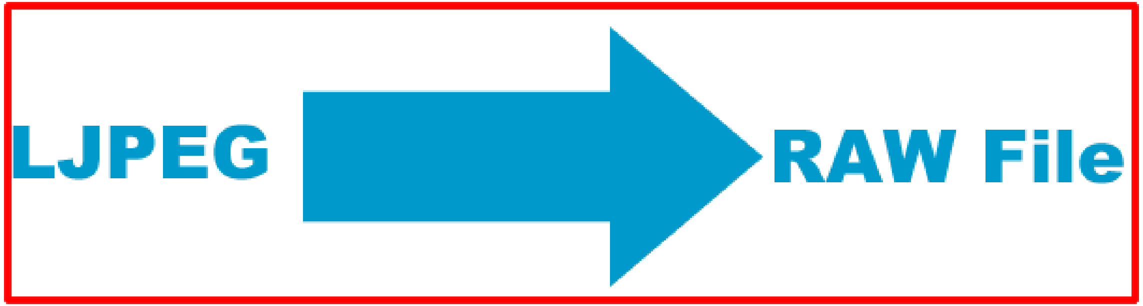
DDSM data base is characterized for having lots of artifacts within the images such as labels.



2.1. LJPEG VISUALIZATION AND DECOMPRESSION

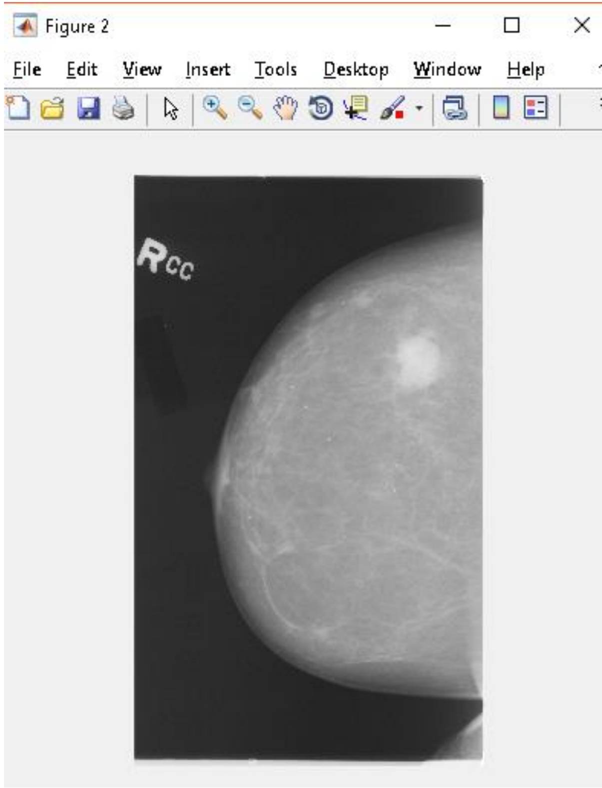
All the images are compressed in the Lossless JPEG format.

C code given by the Stnford University



2.1. LJPEG VISUALIZATION AND DECOMPRESSION

RAW File



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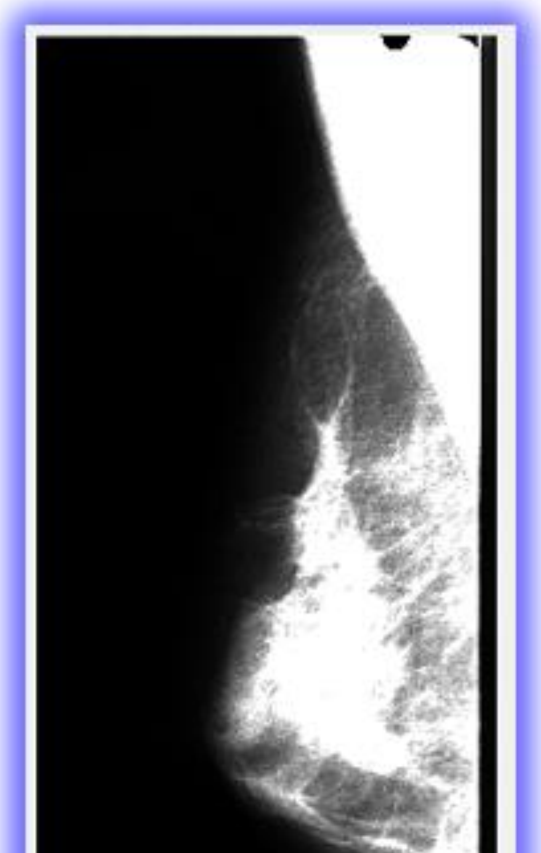
RAW File



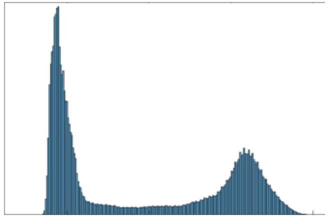
Saturation, and not Open Source :/

Normalized

RAW File

Algorithm to normalize the intensities of the image, and Convert the image to compatible format.

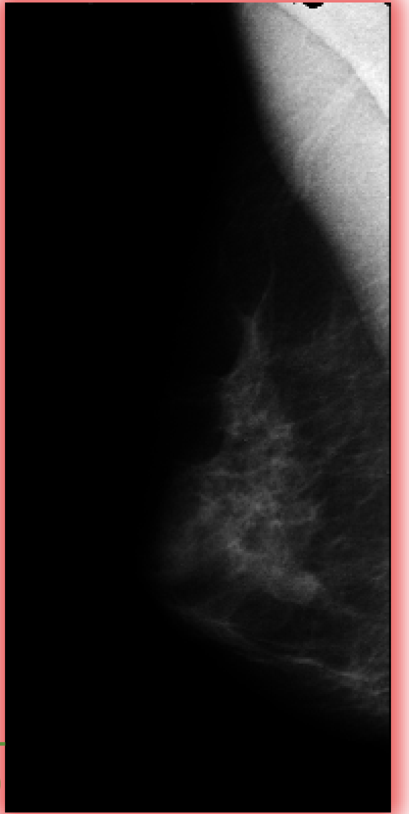
2.1. LJPEG VISUALIZATION AND DECOMPRESSION



$$\bar{x} = \frac{x_1 f_1 + x_2 f_2 + x_3 f_3 + \dots + x_n f_n}{N}$$

RAW File →

Normalized



$$If\ Log2(Maximum\ Value) --\rightarrow \frac{Pixels}{Maximun\ Value}$$

$$Otherwise - \rightarrow \frac{Pixels}{Maximun\ Value - (average + arithmetic\ mean)}$$

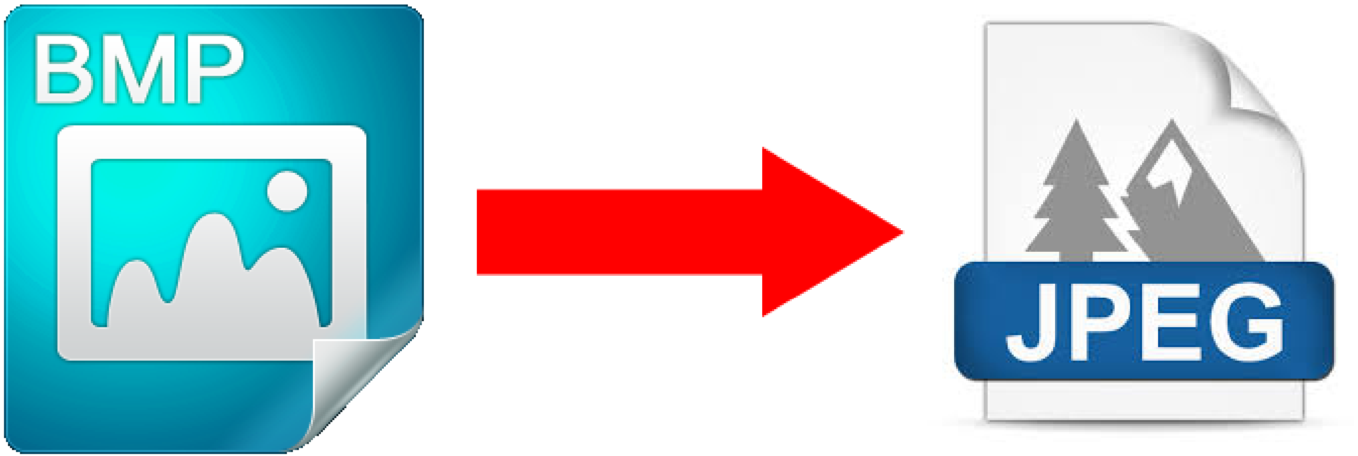
2.1. LJPEG VISUALIZATION AND DECOMPRESSION

Normalized

BMP Format

Ps

2.1. LJPEG VISUALIZATION AND DECOMPRESSION

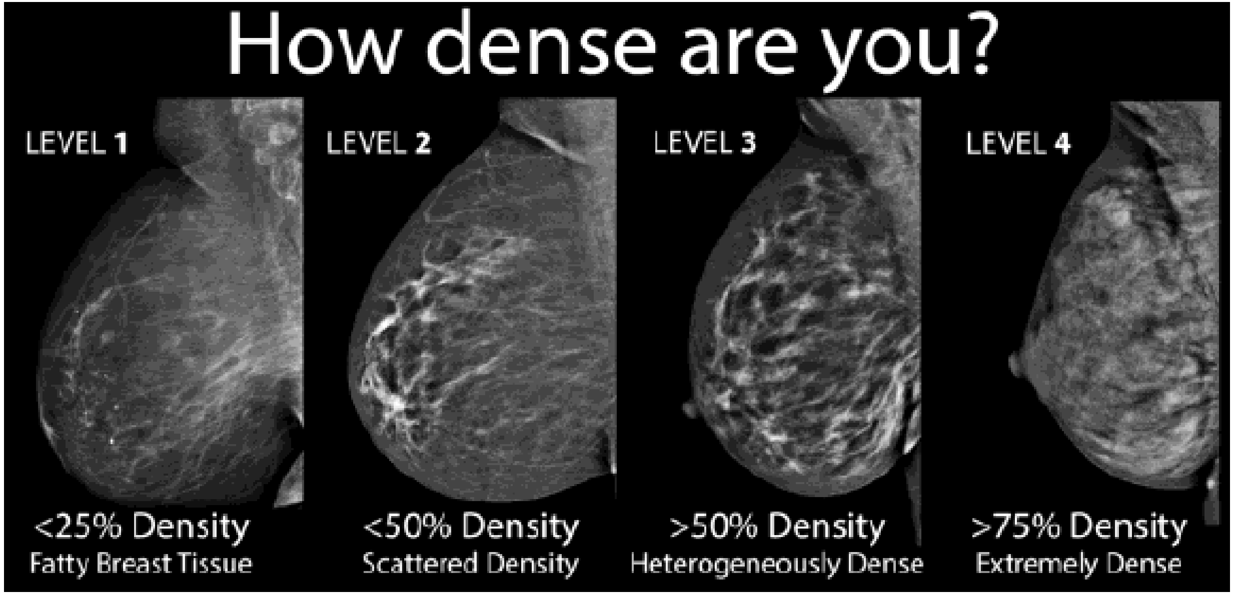


BMP For Image Processing

JPEG for Web Visualization

2.2. BREAST SEGMENTATION

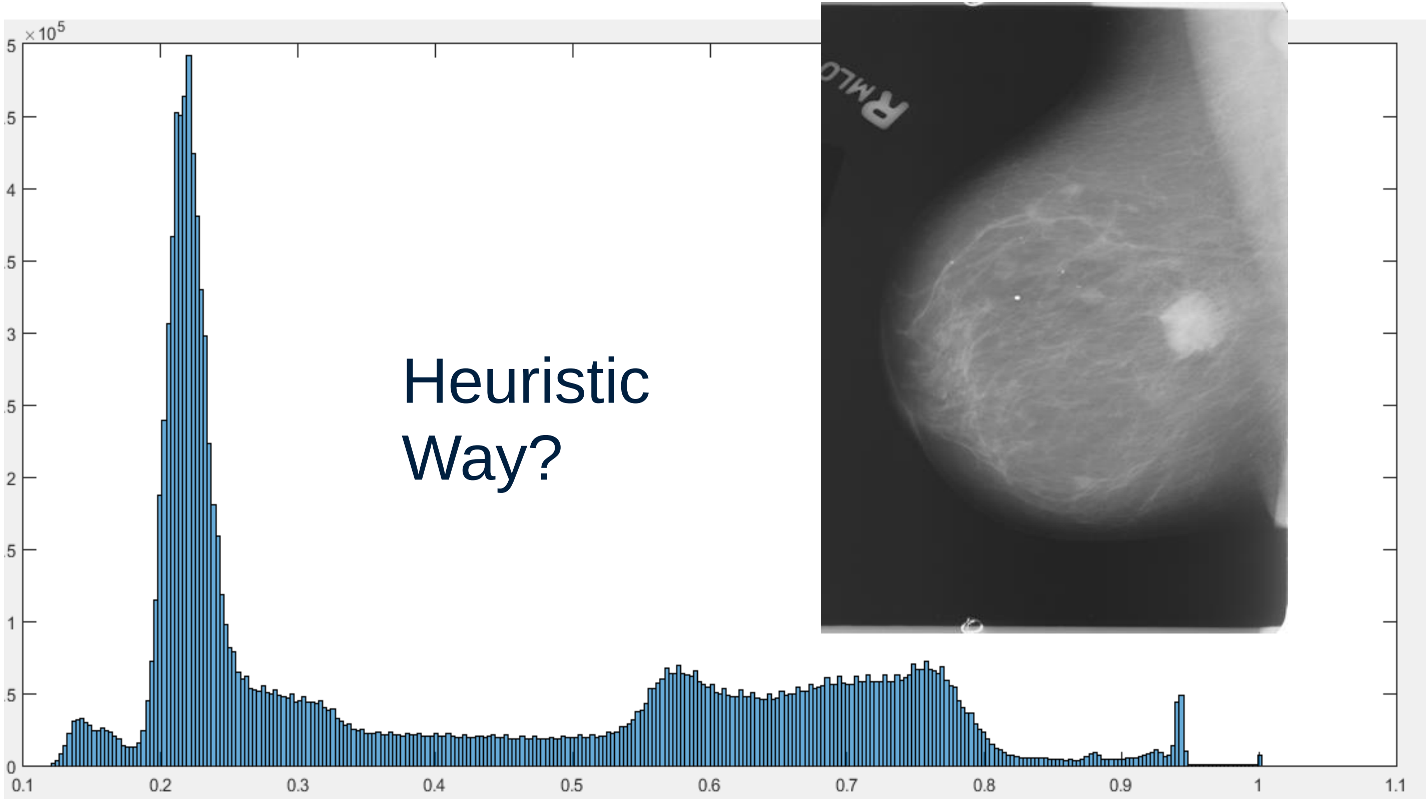
2.2. BREAST SEGMENTATION(WHY?)



1)To reduce the amount of information, remove labels.

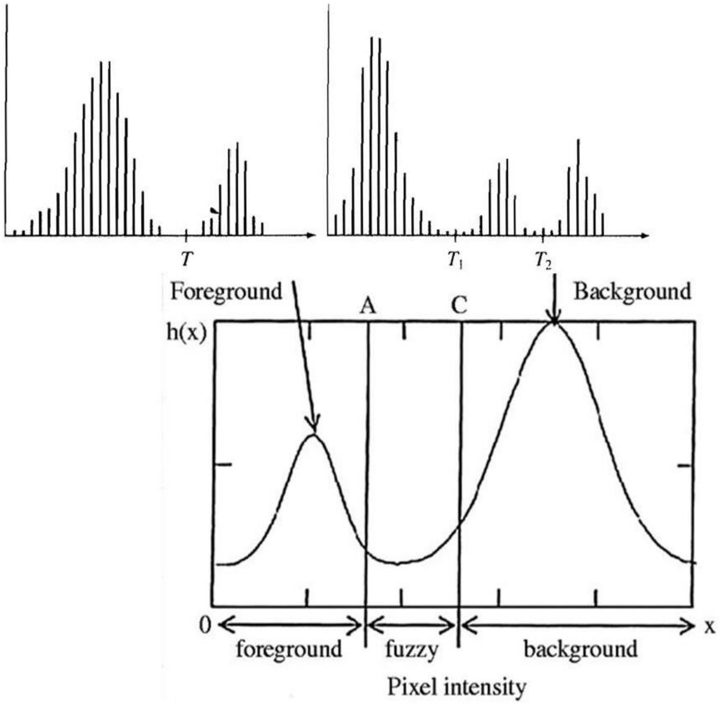
2)The higher density the harder to distinguish the nodule.

2.2.1. OTSU METHOD(OPTIMAL THRESHOLD)



Heuristic Way?

2.2.1. OTSU METHOD (OPTIMAL THRESHOLD)



2.2.1.1.1. Compute the histogram of the image.
2.2.1.1.2. Calculate the probability for each intensity level.
2.2.1.1.3. Initialize Omega and Myu.
2.2.1.1.4. Find the optimal threshold value through the intra-class variance.
2.2.1.1.5. Binarization of the image using the Optimal Threshold.

$$\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t)$$

$$\omega_0(t) = \sum_{i=0}^{t-1} p(i)$$

$$\omega_1(t) = \sum_{i=t}^{L-1} p(i)$$

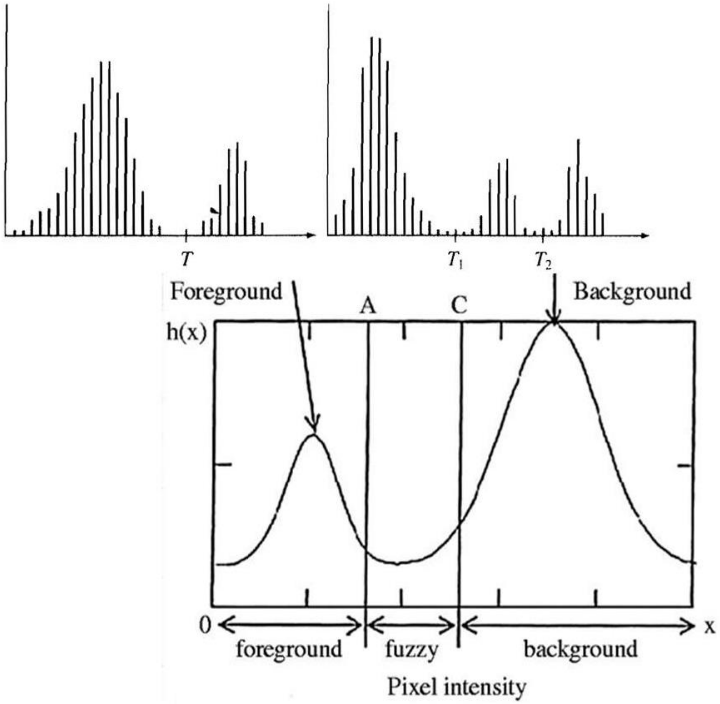
$$\mu_0(t) = \sum_{i=0}^{t-1} i\frac{p(i)}{\omega_0}$$

$$\mu_1(t) = \sum_{i=t}^{L-1} i\frac{p(i)}{\omega_1}$$

$$\mu_T = \sum_{i=0}^{L-1} ip(i)$$

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2$$
$$= \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2$$

2.2.1. OTSU METHOD (OPTIMAL THRESHOLD)



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$$\omega_0(t) = \sum_{i=0}^{t-1} p(i)$$

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$$\omega_1(t) = \sum_{i=t}^{L-1} p(i)$$

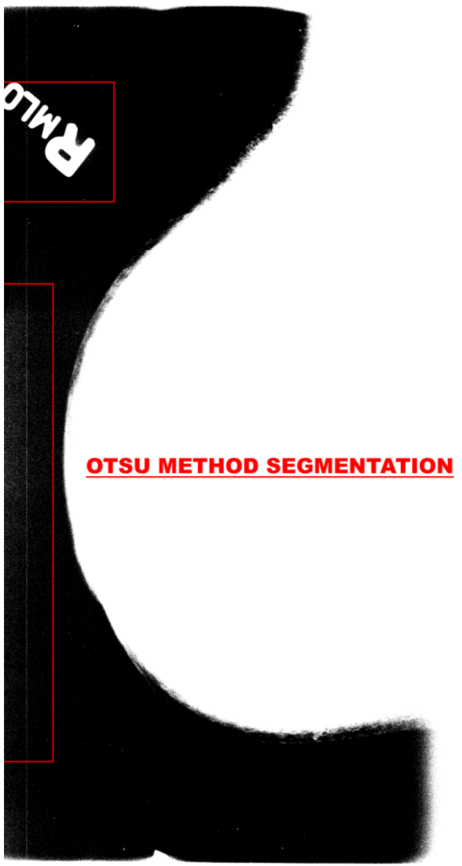
$$\mu_T = \sum_{i=0}^{L-1} ip(i)$$

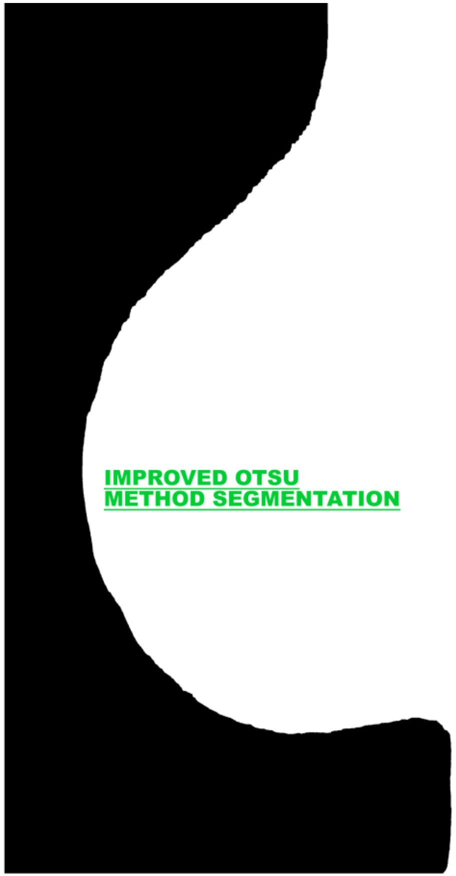
$$\begin{aligned}\sigma_b^2(t) &= \sigma^2 - \sigma_w^2(t) = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \\ &= \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2\end{aligned}$$

2.2.2.AVERAGE FILTER

$$SMA = \frac{p_M + p_{M-1} + \cdots + p_{M-(n-1)}}{n}$$
$$= \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i}$$

Moving Average Filter





2.2.3. EDGE DETECTION

-1	0	+1
-2	0	+2
-1	0	+1

Gx

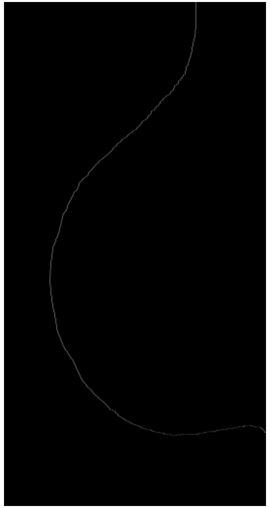
+1	+2	+1
0	0	0
-1	-2	-1

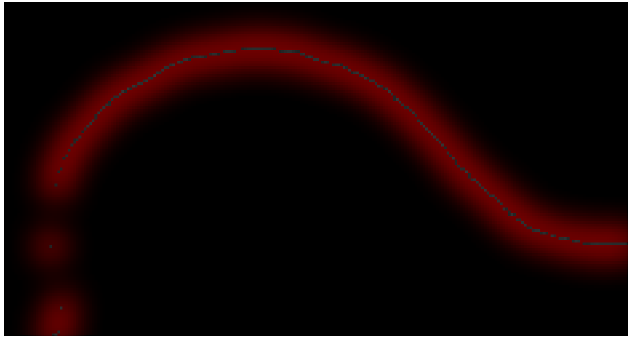
Gy

Sobel Operator

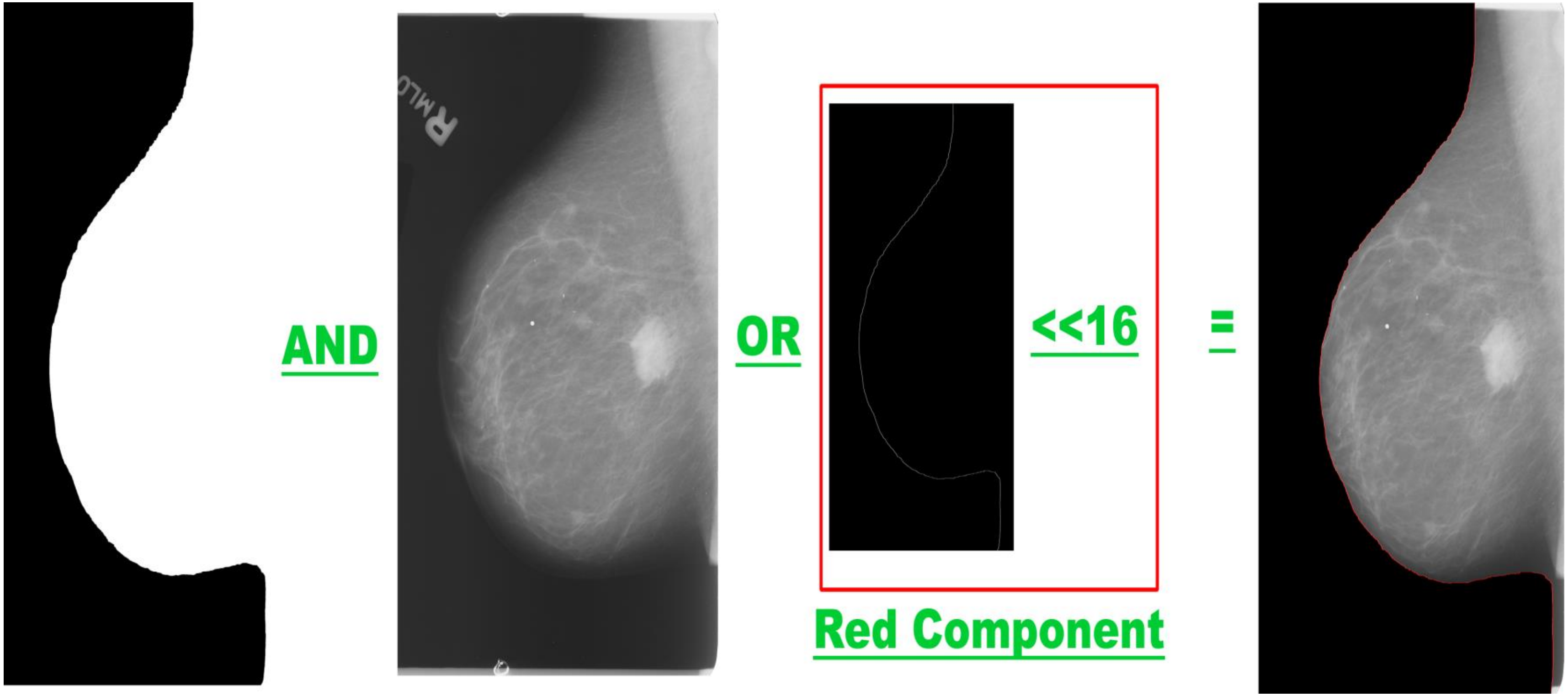
Sobel Gradient Magnitude

$$\mathbf{G} = \sqrt{\mathbf{G}_x{}^2 + \mathbf{G}_y{}^2}$$



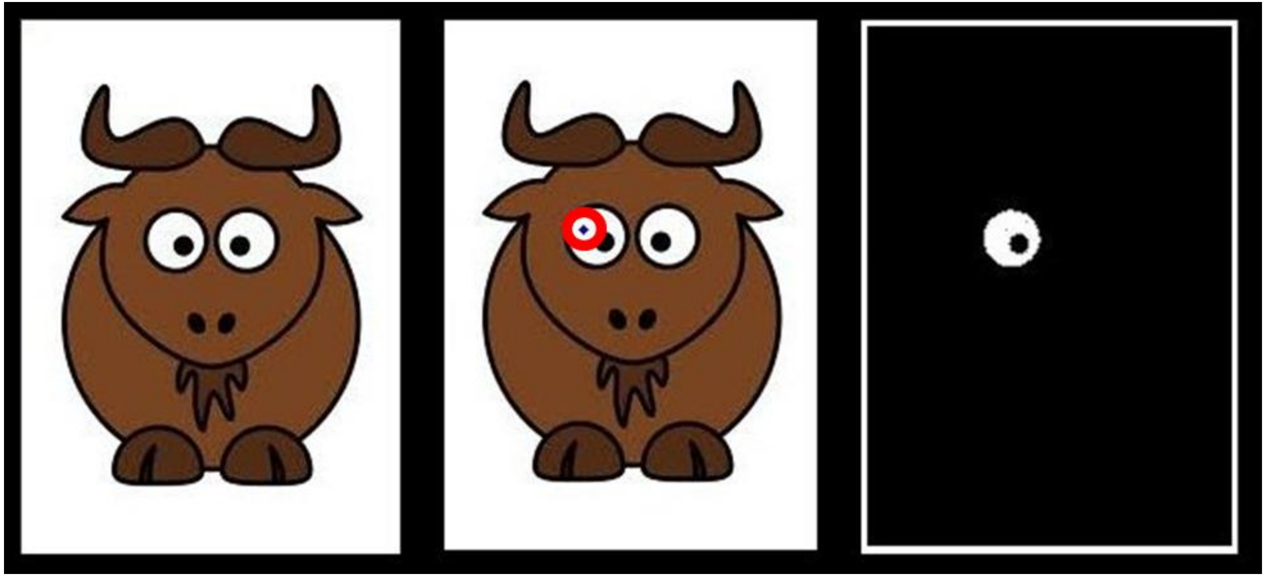


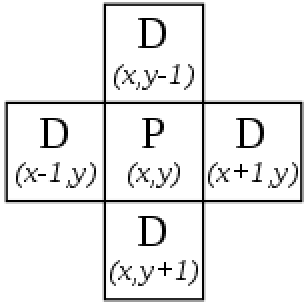
2.2.4. DIGITAL OPERATIONS



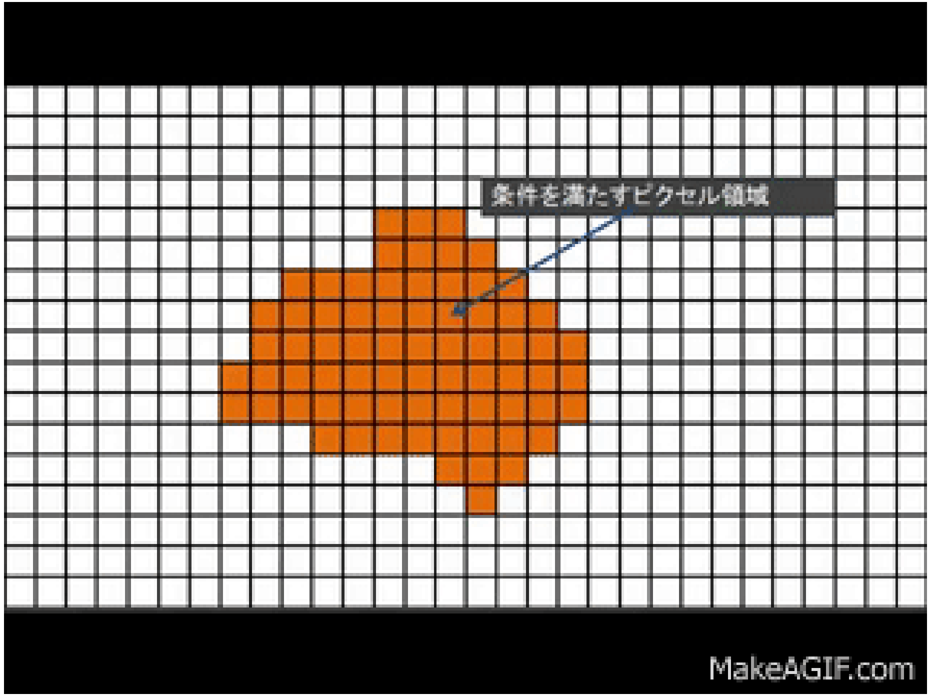
2.3. MASS SEGMENTATION

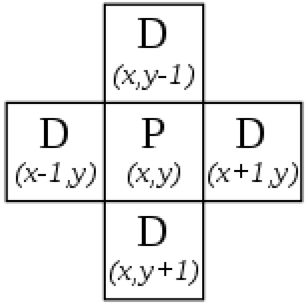
2.3.1. REGION GROWING ALGORITHM





2.3.1. REGION GROWING ALGORITHM

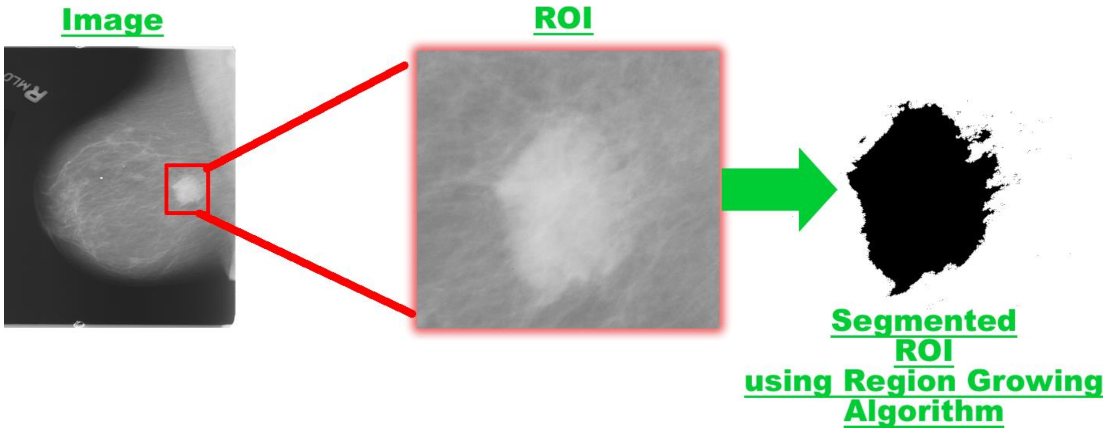


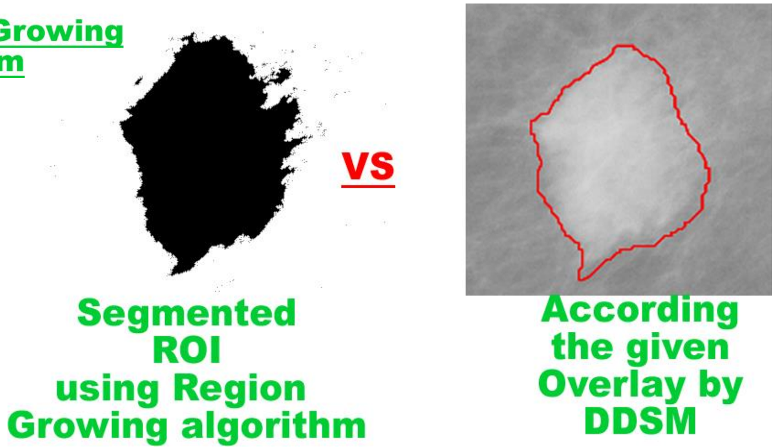


2.3.1. REGION GROWING ALGORITHM

This algorithm examines an initial kernel of pixel which is called the seed points, this seed is compared with its neighbors (pixels around) to determine whether or not the pixel belongs to the region of interest. This algorithm it is an intensive and iterative method to extract similar parts of an image. This region grows until this is block by the stop criteria, which in this case it is the difference between the outside(contour) pixel's intensity and the region's mean, then the minimum difference of the mean and the contour pixel is compared with a threshold, and if this difference is greater than a given thresholds, the algorithms stops. Otherwise the pixels are added to a mask (other image with the same size area of the original initialized with 0s).

2.3.1. REGION GROWING ALGORITHM

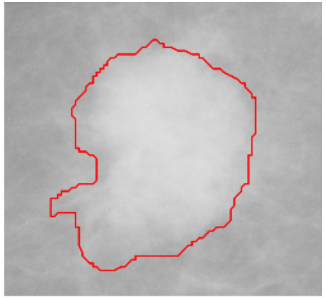




Comparison between Region Growing and the Given overlay by the Database for the Image, B_3084_1.RIGHT_MLO.

Comparison between Region Growing and the Given overlay by the Database for the Image, B_3084_1.RIGHT_CC

VS



Segmented ROI using Region Growing algorithm

According the given Overlay by DDSM

CONCLUSIONS

As a first conclusion, in base of the obtained results, is that there is a considerably number of other methods that could be applied, and wanted to be applied in the project, but for the time it was not possible, such as the K-Means Segmentation, masses classification extracting morphological features that can help the radiologist determine the type of mass (benign, malign), these features could be extracted in base of these first results using mathematical models, Autoencoder or Deep Neural networks. As a first version of a CAD tool, it can be said that the obtained results are satisfying, it is a start that can springboard a new generation of Open-Source CAD tools with the main objective of assisting radiologist to identify the different kinds of masses and its shapes. The project still has a lot work to do, and the help of lot of people that might be interested in continue this work, as I am. All the implemented methods show that the variation of the threshold, a good selection and interpretation of the intensities, it is crucial to perform a good segmentation, and get better results. The constant research in this area and development could take this CAD tool to get better results in the future.

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