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ADJUSTMENT OF NORMALIZED CUT PARAMETERS USING NEURAL NETWORKS

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ABSTRACT

Image segmentation is an important process that used in both quantitative and qualitative analysis of medical ultrasound images, but medical images have features of strong noise and poor contrast and the results of image segmentation may not be good with traditional segmentation methods. in this paper we segment breast ultrasound medical images based on texture features and graph cut ,gray- level spatial dependence matrix(GLSDM) used to extract texture feature parameters ,the similarities matrix is created according to the parameters of texture feature and gray intensity of pixels .normalized cut spectral graph theoretic framework used to segment image depending on the similarity matrix.

This paper introduces a new approach to overcome the problems associated with medical image segmentation such that the proposed approach (Neural Normalized Cut) has the ability to adjust the parameters of normalized cut segmentation technique , Neural normalized Cut has applied for breast ultrasound images , the results show the ability of neural normalized cut to adjust multiple parameters and enhance image segmentation ,especially for medical images.

Keywords: *Medical Ultrasound Images, Texture Feature, Neural Networks, Gray- Level Spatial Dependence Matrix (GLSDM), Graph Cut, Image Segmentation, Thresholding, Normalized cut, Neural Normalized Cut Segmentation, Genetic Algorithms, K-Means, SURF.*

1. INTRODUCTION

Image segmentation is the method that subdivides an image into parts called segments. The level that we reached in division based on the natural of the problem that being solved. We stopped segmentation when we get the objects of interest in an application. Figure.1 shows the relationship between Image understanding, image analysis and image processing. Image analysis mainly focuses to monitor and quantify the intrigued targets in the image in order to get its objective information. Image understanding is one of the basic steps in many researches where the main objective to understand the component of an image and interpret it, image analysis that enters at the middle-level, it focuses on quantifying, expression and description of target. finally, image processing is relatively low-level operations and mainly operated on the pixel-level. For example, in medical image processing identification of tumor is enough and no further processing is needed. on the left side, in some cases we need to know image segments as a pre-processing step.

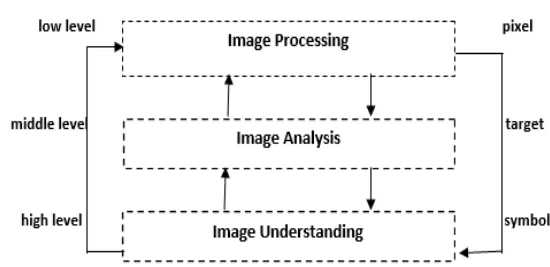

Figure1 the Three-Dimension Chart of Image Designing

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The image segmentation techniques can be sorted into two types dependent on image characteristics.

A. Similarity based method: This method divides the image into objects or segments having similar set of pixels. The segmentation techniques that depend on this method are: Thresholding techniques, region-based method, clustering technique and region growing techniques.

B. Discontinuity based method:
In this technique the image is divided into segments depended on discontinuity such as edge-based segmentation techniques.
Many ways have been introduced to resolve medical image segmentation containing using of k-means, thresholding, level-sets, region growing, each one from before methods have its advantages and disadvantages depended on dataset used and the natural of problem. This search will make a great impact in medicine, diagnosis, and treatment many diseases such that the integration between various techniques can enhance the performance of images.

This paper is organized as:
: in section 1 introduction. In section2 a brief survey about segmentation techniques .in section 3 we briefly discuss used feature extraction techniques. In section 4 we discuss our proposed approach in detail, experimental results, and results discussion.

2. ABRIEFSURVEYABOUTSEGMENTATIO N TECHNIQUES

As shown in Figure.3 segmentation techniques were divided as follow:

2.1. Region Based Method [2-4]: divide the segmented image into clusters based on similarity.

2.1.1 Threshold technique

Thresholding techniques [5] are the most straightforward techniques for image division. These techniques separate the pixels in image based on their intensity level. These strategies are utilized in all images that have lighter items than background as shown in figure.2. The choice of these strategies can be manual or programmed. There are three types of thresholding [6, 7]

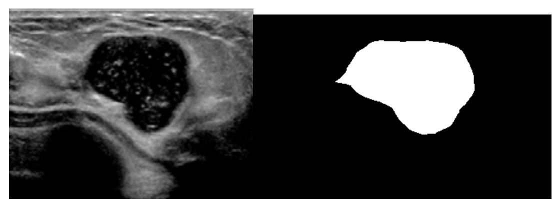
A. Global Thresholding: This is made by utilizing any fitting threshold value *T*. This value of *T* will be constant for all image. on the basis of *T*, the output image $d(x, y)$can be generated from the input *image* $p(x, y)$.

$$d(x,y) = \begin{cases} 1, & if p(x,y) > T \\ 0, & if p(x,y) \le T \end{cases} \quad (1)$$

B. Variable Thresholding: in this type the value of *T* can changed. this threshold contains two types (local threshold, adaptive threshold).

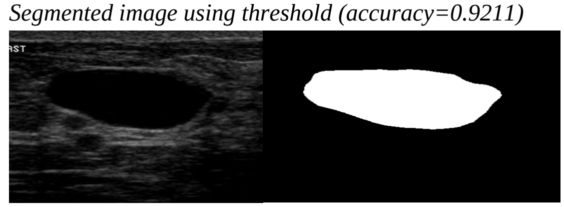
C. Multiple thresholding: in this type there are many threshold values as *T1* and *T2*.in this case the output image calculated using this equation

$$d(x,y)= \begin{cases} a, & if p(x,y) > T1 \\ b, & if p(x,y) \le T1 \\ 0, & if\ p(x,y) \le T0 \end{cases} \quad (2)$$



Original image *Gold image*

Segmented image using threshold (accuracy=0.9211)



Original image *Gold image*

Segmented image using threshold (accuracy= 0.9093)

Figure.2 Threshold Segmentation for Ultrasound Breast Image

2.1.2. Region growing

Region growing[8]is one of well-known methods. Begins with a pixel and will continue including the pixels depended on similarity, to the region, repeat until all pixels have a place with some region.

2.1.3. Normalized Cut (N_Cut)

Weiss[9]provide us with a brief survey of the graph cut techniques for segmentation that are depended on eign vectors of the affinity matrix, one of the best method introduced was normalized cut[10] that deal with image as a graph and divide it based on similarity such that it calculates the similarity within the groups, and also calculates the dissimilarity between different groups depended on eign value.
Let $G = (V, E)$ be a weighted undirected graph where V(nodes) and E (edges), and the weight function of similarity $w = (i, j)$ is lied on the edges between the points i and j. The graph is segmented based on the grouping approach. Such that the similarity within the group is high and the dissimilarity between different groups is low and the image is segmented using eign vectors. In brief the graph $G = (V, E)$ is segmented to two groups A and B such that
$A \cup B = V$, and$A \cap B = \emptyset$. By deleting edges that connect the two groups the degree of dissimilarity (weight) or called cut is calculated as

$$cut(A, B) = \sum_{u \in A, v \in B} W(u, v) \quad (3)$$

The value of this cut should be small to get best segmentation. a measure of normalized cut or disassociation can calculate the cost of cut as follow:

$$N - cut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)} \quad (4)$$

Such that,
$assoc(A, V) = \sum_{u \in A, t \in V} W(u, t)$, in the same way a measure of all normalized association within the sets defined as

$$Nassoc(A, B) = \frac{cut(A, A)}{assoc(A, V)} + \frac{cut(B, B)}{assoc(B, V)} \quad (5)$$

Such that,$assoc(A, A)$, $assoc(B, B)$are edges weight that connecting all nodes within the graph $A \cup B$ .so, in the grouping approach two things must be achieved

a) Association with in two groups must achieve maximum value.
And,

b) Disassociation between two groups must achieve minimum value.

The normalized cut is used in grouping partition based on these steps[10]:

- $G = (V, E)$Is built for all images and the weight is calculated.
- Solve $(D - W)x = \lambda Dx$ for eign vectors, such that D is $N \times N$ matrix.
- Use eign vectors to find the dividing points.
- Check the accuracy of the cut.
- Repartion the graph if necessary.

In previous steps many parameters such as threshold and weight function that affects in graph segmentation accuracy must be adjusted to achieve high accuracy such that

- The radius(r).
- The number of segments (N_S).
- The rate(R).
- Edge variance (E_v).

These parameters (r, E_v, R) used to compute the similarity matrix.

2.1.4. Clustering based segmentation technique

The clustering-based procedures are the strategies, which section the image into groups having pixels with similar properties. Information clustering is the strategy that separates the information components into groups with the end goal that components in same group are more like each other. There are two fundamental classes of grouping techniques: Hierarchical strategy and Partition based technique. The various leveled strategies depend on the idea of trees. The root of the tree represents the whole database and the internal nodes represent the clusters. On the opposite side the partition-based strategies use enhancement techniques iteratively to limit a goal work. In between these two techniques there are different algorithms to discover clusters. There are essential two types of clustering[11, 12].

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Hard Clustering: Hard clustering is a straightforward strategy that separates the image into groups such that one pixel can only has a place with a single group. These strategies use enrolment capacities having values either 1 or 0 for example one either certain pixel can have a place with specific cluster or not. A case of a hard clustering-based procedure is k-means grouping based method known as HCM. In this procedure, all the centers are computed then each pixel is assigned to nearest center.

Soft clustering
Soft clustering is progressively common kind of clustering because in natural life exact segmentation is not reached because of image noise, such as fuzzy c-means clustering in this strategy pixels are divided into clusters depended on partial relationship. For example, one pixel can have a place with more than one group. This procedure is more adaptable than different methods[11].

2.2. Edge Based Method
Divide the segmented image based on discontinuity[13]

2.2.1. Artificial neural network

The artificial neural system-based segmentation techniques mimic the learning procedures of human mind with the end goal of decision making. Now days this technique is utilized for medical image segmentation. It is used to isolate the required object from background. A neural system is made of substantial number of associated hubs and every association has a specific weight. This strategy has two fundamental stages: features extraction and segmentation by neural system[3].

2.2.2. Fuzzy logic segmentation technique

Fuzzy logic is a multi-valued logic which is like human reasoning. It has the capability of combining human heuristics into PC, Fuzzy logic has been connected in all Controls of medicine to help in decision making strategy.

2.2.3. Genetic algorithm technique

The genetic algorithm is a method for solving both unconstrained and constrained optimization problems that depending on natural selection, You can use the genetic algorithm to solve all of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, no differentiable, stochastic, or highly nonlinear. The genetic algorithm can address problems of mixed integer programming, where some components are restricted to be integer value.
The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

- Selection: rules select the individuals, called parents that contribute to the population at the next generation.
- Crossover: rules combine two parents to form children for the next generation.
- Mutation: rules apply random changes to individual parents to form children.

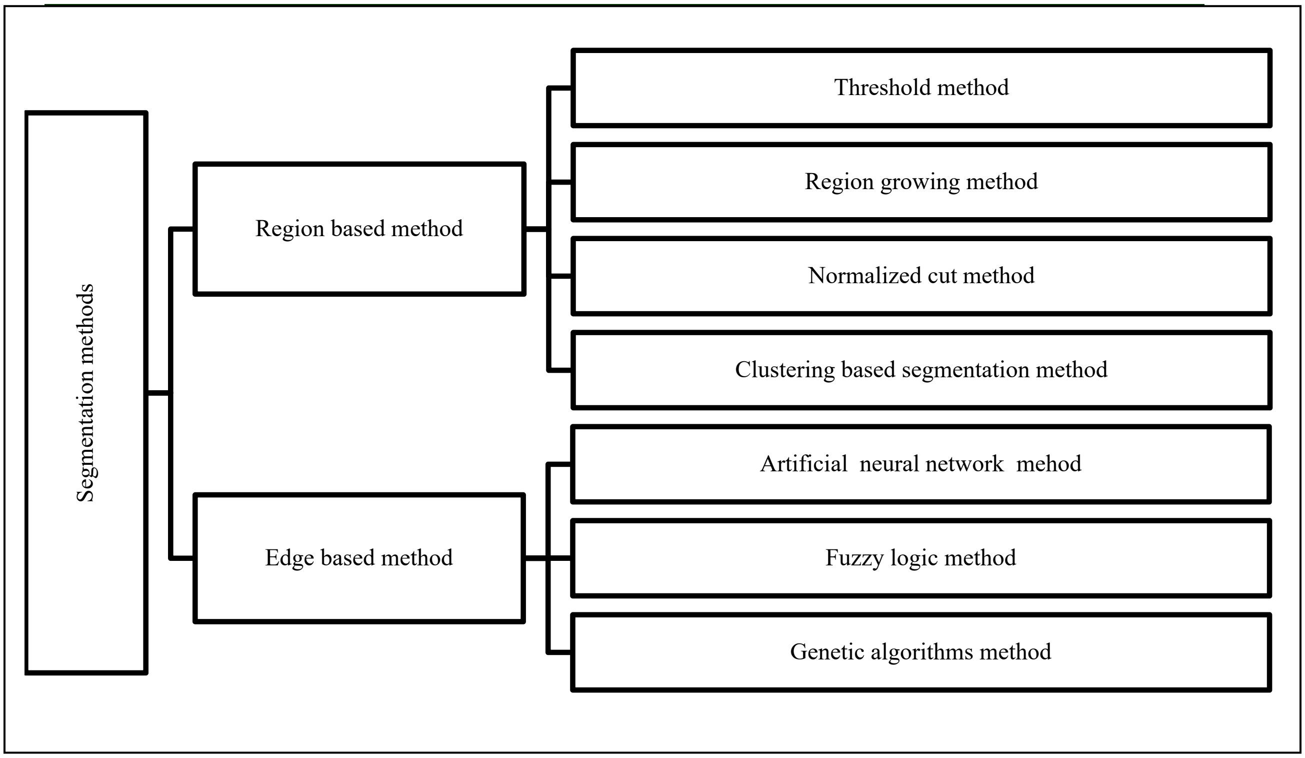

Figure.3 Image Segmentation Methods

2.3 Comparison Between Used Segmentation Techniques

Segmentation technique	Description	Advantages	Disadvantages
Thresholding Method	Depends on the image histogram to discover specific threshold value	-The simplest segmentation technique, such that it needs few information - true for every kind of signal processing	-Depended on histogram peaks -Thresholding always throws out information which you will never be able to use again, as you reduce the information to a binary variable. I.e.: instead of a value from 0–255, you have a {0,1} set
Normalized cut method	Consider an image as an undirected graph and each edge is assigned with a non-negative weight	-efficiency -rapid calculation	-High computational cost especially for images with large size -bad for object boundaries

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3. RELATED WORK

3.1. Speeded Up Robust Features

SURF[14, 15] is a patented algorithm utilized generally in computer vision assignments and tied to object detection purposes. SURF falls within the category of feature descriptors by extracting key points from different regions of a given image and thus is very useful in finding similarity between images.

The algorithm works as follow:

A) Find features/key points that are likely to be found in different images of the same object. Those features should be scale and rotation invariant if possible.

B) Find the right "orientation" of that point so that if the image is rotated according to that orientation, both images are aligned regarding that single key point.

C) Computation of a descriptor that has information of how the neighborhood of the key point looks like (after orientation) in the right scale.

3.2. Texture Feature Extraction

Gray- level spatial dependence matrix (GLSDM) is one of the most critical strategies to calculate texture features[16], which was presented by Haralick. the GLSDM functions characterize the texture of an image by calculating how regularly set of pixels with values and in indicated relationship happen in an image, making a GLSDM and after that extracting statistical measures from this matrix.
Gray- level spatial dependence matrix (GLSDM) is a matrix of relative frequencies Pij which two neighboring resolution cells isolated by distance d occurs in the image, one with gray tone i and the other with gray tone j.
Features are calculated from gray- level spatial dependence matrix (GLSDM) is in the directions 0, 45, 90, and 135 degrees as follow:

$$p(i,j\backslash d,0°)=\{(x,y)\backslash f(x,y)=i,f(x+dx,y+dy)=j,dx=d,dy=0\} \tag{6}$$

$$p(i,j\backslash d,45°)=\{(x,y)\backslash f(x,y)=i,f(x+dx,y+dy)=j,dx=-d,dy=d\} \tag{7}$$

$$p(i,j\backslash d,90°)=\{(x,y)\backslash f(x,y)=i,f(x+dx,y+dy)=j,dx=0,dy=d\} \tag{8}$$

$$p(i,j\backslash d,135°)=\{(x,y)\backslash f(x,y)=i,f(x+dx,y+dy)=j,dx=d,dy=d\} \tag{9}$$

Where $f(x,y)$ is a gray image with size $N\times N$,(x,y) is the coordinate of pixel in the image,dx is offset in the row and dy is offset in the column.
We use a set of texture features.

a) Contrast: a degree of the intensity difference between a pixel and its neighbors.
b) Energy: the sum of squared elements in the GLSDM.
c) Homogeneity: a value that measures the closeness of the distribution of elements in the GLSDM to the GLSDM diagonal.

We have 3 features in 4 directions 3*4=12 for n=35 ,then we have feature matrix of size 12*35 , since we use matlab functions “gray matrix” to calculate co-occurrence matrix and “gray coprops” to estimate the features from the GLSDM.

4. PROPOSED APPROACH

4.1. Data Set

In our experiments we use 35 ultrasound breast images, which segmented before by an expert, the images have different size ranged between 230*390 up to 580*760 pixels. Ultrasound images are very hard in segmentation because of noise and contrast.

4.2. Pre-processing Process

In pre-processing process, we use median filter (using matlab function medfilt2) to delete noise from image to improve the results of later processing, median filtering is used in image processing because in removing noise it preserves the edges of the image.

4.3. Proposed Approach (N_Ncut)

We developed our approach because of the previous search problem in image segmentation such as many segmentation techniques have parameters that need to be adjusted , User feedback in medical images widely ignored, and Computationally inefficient, especially when a large number of images must be processed sequentially in real time.
in brief, our algorithm use image characteristics to supervise the neural networks in order to segment images based on image threshold T ∈{0, 1,….,255} the network is trained based on the features that extracted from the training images .

The introduced algorithm uses neural network to automatically adjust normalized cut parameters based on image characteristics, our algorithm contains two phases

4.3.1 The training phase:

In the training phase for every set, different five images used to train the network through:

4.3.1.1. Feature extraction

In this step randomly five training images are selected to train the network as follow:

- Read the first image i .
- Pass i to SURF to return a set of key points (p) inside i.
- Remove surf points (p) whose coordinates are larger than the size of image (i).
- Estimate the mean for every point.
- Around each point a rectangle W of size $N \times N$ is created to extract features and store these features in a matrix $F1$ containing p rows that contains
  - a) The mean μ_W.
  - b) The standard deviation σ_W
  - c) A set of texture features from (GLSDM) in the direction 0
    - Contrast
    - Energy
    - Homogeneity
  - d) Estimating the discrete cosine transform (C_W) of W.
  - e) The features μ_{CW},σ_{CW}, and GLSDM texture features of C_W.
  - f) The features μ_{vm}, σ_{vm}, and the texture feature is calculated
- Hence, the size of $F1$ matrix is p*15.
- Based on the statistical measures such as mean, median, maximum, minimum, variance, standard deviation final features are calculated in a matrix f from F.
- Optimum parameters stored in matrix f.

4.3.2 the testing phase

In this phase the remaining images used to test the neural network, and the normalized cut parameters are calculated as follow:

- Read the first test image I.
- Extracting features from I .
- Normalized cut parameters are calculated from I using its features.
- A matrix is constructed where each column represents a result for one parameter.
- Every final parameter output is estimated as follow:
  1. Mean, standard deviation, and median are calculated for the first column(N_S1).
  2. Mean, standard deviation, and median are calculated for the second column(N_S2).
- The last parameters of (N_S1) and (N_S2) are used in I segmentation using normalized cut.
- The segmented image B is given to expert for correction.
- The corrected image (G) is used to update image parameters (N_S1, N_S2)
- Any row that already found in F removed automatically from f using cosine similarity.

$$cosinesim(i,j)=\frac{f(i,k)*F(j,k)}{\|F\|\|f\|} \quad (10)$$

For i=1,………,N and j=1,……….,M and k=1,…………,L ,where N is the number of (f)rows ,and M the number of $(F\ )$rows, and L the number of columns in f and F.

- When using a new image for testing all the above steps repeated automatically.

5. EXPERIMENTAL RESULTS

- In this part we explain our results such that five images selected randomly for training and the remaining 30 images used for testing (35 ultrasound images used to evaluate the accuracy of our algorithm).

- We repeated every experiment five times and the output of the runs written in table I.
- We use three distinctive results for each group
  a) The normalized cut results using (N_S=5).
  b) The normalized cut results using (N_S=8).
  c) The normalized cut results using (N_S=10).

6. QUALITY MEASURES

In our algorithm we have two segments B (produced by the proposed algorithm), and G(prepared by expert), to estimate the accuracy of proposed approach we use

- Jaccard index

$$J(B,G)=\frac{|B\cap G|}{|B\cup G|} \quad (11)$$

7. RESULTS DISCUSSION

as written in table 2 the introduced algorithm(neural normalized cut segmentation (N-Ncut)) in the first training group the average of Jaccard index of N_Ncut is 60%comparing to 59%,51%,and 58% in N-S5,N_S8 , and N_S10 so we get the best optimum segment found using neural normalized cut in this group of images (figure.4), in the second training group the value of the number of N-cut segments equal to 8 is the best selection for this group of images but this require hard manual selection to get this best value ,figure.5 shows segmentation sample for ultrasound breast images

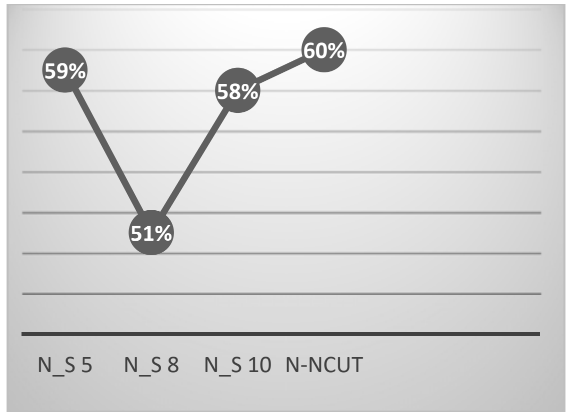

Figure 4: Comparison of the Jaccard accuracy obtained with N_Ncut and with N_S5, N_S8, and N_S10 in the first training set

8. CONCLUSIONS

Image segmentation is a very important process because of its use in several practical applications, such as medical imaging. In any segmentation technique, there is one or more parameter that needs to be adjusted in order to achieve maximum segmentation accuracy. This process is impractical especially when large number of images need to be segmented. In this research we focus on automatic adjustment of multi parametric segmentation techniques such that we automatically assign normalized cut parameters based on images features .in the training stage algorithm randomly select a set of images from all images, and then extract features from these images, these features used to calculate the normalized cut parameters for new images in the testing stage. As shown in table1 Our approach has many advantages for example high accuracy, rapid operation, and low cost. The only drawback of our approach is that the neural normalized cut effective in assumptions made by the network than others.

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Table 1 Shows the Advantages and Disadvantages Between Our Proposed Approach and Other Approaches.

Segmentation technique	Advantages	Disadvantages
Thresholding Method	-The simplest segmentation technique, such that it needs few information -true for every kind of signal processing.	-Depended on histogram peaks. -Thresholding always throws out information which you will never be able to use again, as you reduce the information to a binary variable. I.e.: instead of a value from 0–255, you have a {0,1} set.
Normalized cut method	-efficiency -rapid calculation	-High computational cost especially for images with large size -bad for object boundaries
Neural normalized cut(N-Ncut)	-high accuracy -rapid operation -low cost	- a huge number of images are required to train the network -approach is only good in the assumptions made by the network.

Table 2 Results For Breast Ultrasound Image Segmentation :N_S5,N_S8,And N_S10 Are Different Values For Normalized Cut Segmentation ,N_Ncut Is The Neural Normalized Cut Segmentation (Proposed Approach)Where The Parameters Are Calculated Using Neural Networks (Jaccard Index To Calculate The Accuracy)

Training	***First group***	***Second group***	***Third group***	***Fourth group***	***Fifth group***
Method	***Jaccard Index***				
N_S 5	*59%*	*43%*	*57%*	*60%*	*69%*
N_S 8	*51%*	*69%*	*56%*	*65%*	*67%*
N_S 10	*58%*	*51%*	*73%*	*74%*	*73%*
N-Ncut	*60%*	*61%*	*72%*	*76%*	*78%*

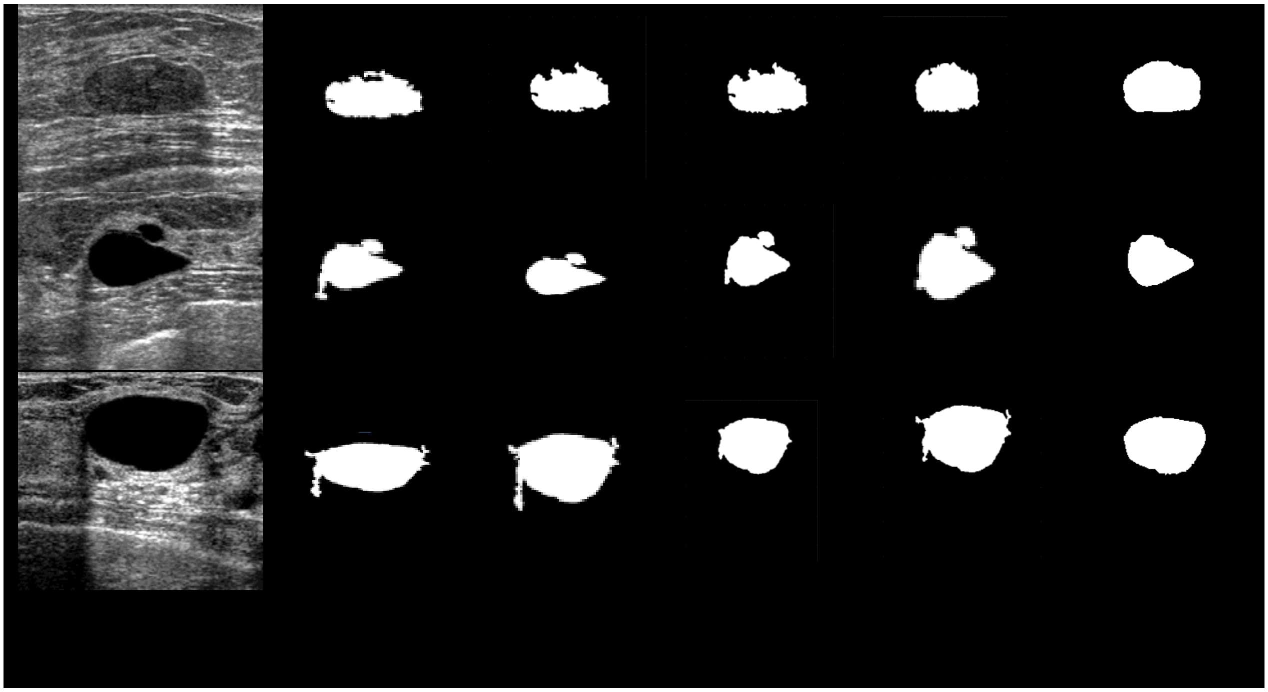

Figure.5. Some Segmentation Results (Left to Right): Original Image, N_S5, N_S8, N_S10, N-Ncut, And the Gold Standard Image Prepared by Expert

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