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Improving Medical Image Perception By Hierarchical Clustering Based Segmentation

Arul N. Selvan, Reza Saatchi and Christine M. Ferris.

***Abstract*— It has been well documented that radiologists' performance is not perfect: they make both false positive and false negative decisions. For example, approximately thirty percent of early lung cancer is missed on chest radiographs when the evidence is clearly visible in retrospect [1]. Currently Computer-Aided Detection (CAD) uses software, designed to reduce errors by drawing radiologists' attention to possible abnormalities by placing prompts on images. Alberdi *et al* examined the effects of CAD prompts on performance, comparing the negative effect of no prompt on a cancer case with prompts on a normal case. They showed that no prompt on a cancer case can have a detrimental effect on reader sensitivity and that the reader performs worse than if the reader was not using CAD. This became particularly apparent when difficult cases were being read. They suggested that the readers were using CAD as a decision making tool instead of a prompting aid. They conclude that "incorrect CAD can have a detrimental effect on human decisions" [2]. The goal of this paper is to explore the possibility of using Hierarchical Clustering based Segmentation (HCS) [3], as a perceptual aid, to improve the performance of the reader.**

Index Terms— *Clustering, Segmentation, Perception.*

I. Introduction

A capability of the human vision system is the ability to generate multiple solutions of varying resolutions. For example, given an anatomical image of the cross-section of a skull, at a coarse level a radiologist can classify the image as regions belonging to soft tissues and the skull bone. At a fine level different types of soft tissues are also identified. At a still finer level, the radiologist will also be able to distinguish the dissimilar regions within the same tissue type. A segmentation procedure has been developed to mimic this capability of human vision. The developed hierarchical clustering based segmentation (HCS) procedure automatically generates a hierarchy of segmented images. The hierarchy of segmented images is generated by partitioning an image into its constituent regions at hierarchical levels of allowable dissimilarity between its different regions. At any particular level in the hierarchy, the segmentation process will cluster together all the pixels and/ or regions which have dissimilarity among them less than or equal to the dissimilarity allowed for that level. The HCS procedure produces a huge amount of visual information. A Graphical User Interface (GUI) was designed to present the HCS output in an informative and effective way for the user to view and interpret.

The rest of the paper is organized as follows. Firstly the operation of HCS process is outlined briefly. Secondly the facilities offered by the designed GUI to display the original image data and the HCS output is given. Then the performance of the HCS process in highlighting abnormalities is discussed. Finally the possibility of using HCS as a perceptual aid, to aid radiologists is discussed.

II. Overview of Hierarchical Clustering Based Segmentation

In the hierarchical clustering based segmentation (HCS) an image is partitioned into its constituent regions at hierarchical levels of allowable dissimilarity between its different regions. At any particular level in the hierarchy, the segmentation process clusters together all the pixels and/or regions that have dissimilarity among them less than or equal to the dissimilarity allowed for that level. It should be noted that HCS, unlike other segmentation methods [4], is not an iterative optimization process. Instead at each level HCS yield an optimized segmentation output related to the dissimilarity allowed for that level. The algorithmic diagram, shown in Fig. 1, illustrates the overall operation of HCS [3]. The HCS process yields a merge tree. Based on the merge tree a GUI can display the hierarchy of merges.

III. GUI Facility for Displaying HCS Results

The HCS process generates a hierarchy of segmentation results, associated with a set of dissimilarity values. The segmentation results are stored at the end of the HCS processing. Subsequently the GUI can be used to reproduce the resulting segmentation images associated with a dissimilarity value instantaneously.

Making use of the GUI, the user can inspect how the merging process evolves. The user can interactively choose the dissimilarity level at which he wants to view the segmentation results. At a low value of dissimilarity, the segmented image will show many varied regions similar to the original image. When choosing a high value of dissimilarity the image will only show regions which are significantly different.

The original image may be displayed alongside the processed image showing regions of dissimilarity. And a dual cursor facility provided by the GUI will allow the user to correlate the segmentation results with the original image data. This enables the clinician to improve his ability to identify regions having subtle differences or dissimilarities.

The GUI also helps the user to differentiate dissimilarities

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in the image down to a single pixel level by providing him the facility to highlight pixels belonging to the same region which might occur across the image.

The GUI is designed in such a way as to make it easy for the user to view all the different solutions and select the most suitable. The easy viewing and scrutinizing of segmentation results is achieved by the GUI by having the following facilities :

1) The different segmentation results can be viewed by using a slider bar giving the dissimilarity index.
2) Individual region properties like the number of pixels, the lowest, highest and average pixel value and the distribution of the pixel values within the region can be scrutinized.
3) The original image or another segmented image at different level of dissimilarity can be compared with the segmented image by displaying them alongside each other and a dual cursor moves simultaneously on both the images.
4) In order to allow the users to quickly display the segmented image the GUI provides a gallery of the set of segmented images. The user can click on any one of the thumb nail images to have it displayed on the main window.

The image shown in Fig. 2 gives a screen shot of the GUI and the user controls provided for the above listed facilities.

IV. Performance of the HCS in Highlighting Abnormalities

Medical image segmentation is a difficult task because of issues such as spatial resolution, poor contrast, ill-defined boundaries, noise, or acquisition artifacts [5]. The medical images in the Fig. 3 and Fig. 4 illustrate the difficulty to accurately delineate the boundaries of the different regions. Fig. 3 shows a CT image of a section of the brain. The image area within the region of interest (rectangular area outlined in black) is made up of three different types of regions viz. Grey matter, White matter and the stroke affected area. The stroke affected area has been outlined in white by an expert. Fig. 4 shows the segmentation result obtained by Hierarchical Segmentation (HSEG) version 1.1 [6]. HSEG is chosen as an illustration since it is one of the very few studies with an approach that is similar to our HCS process.

Fig. 4 illustrates the difficulties faced by the HSEG process to segment the medical image. Although the image pixels within the region of interest (ROI), have been segmented into three classes, color coded as red (the diseased area), green (White matter) and blue (Grey matter), it has misclassified some of the pixels not belonging to the diseased area as being diseased as well. This can be seen by the presence of red colored pixels at the other end of the ROI; *i.e.* outside the area outlined by the expert.

Fig. 5 shows the segmentation result based on our HCS. In this case the process has successfully delineated the three different types of regions viz. Grey matter, White matter and the stroke affected area. In fact the HCS process delineation of the stroke affected area is much more precise than that of visual inspection by an expert. This is evident from Fig. 6, from where it could be seen that the expert's outline of the diseased area (white outline) is only very approximate, which includes substantial part of the healthy part of the image.

Comparing the segmentation results of Fig. 4 and Fig. 5 it can be seen that the HSEG process segmentation (Fig. 4) is suboptimal while the HCS process is able to achieve a smooth segmentation as shown in Fig. 5.

V. HCS as a Perceptual Aid, to Assist Radiologists

A. Mammograms

Dense breasts contain more glandular and connective tissue. Less dense breasts are mainly made up of fat tissue. Breast cancer itself is made up of dense tissue. This means that on a mammogram, a tumor is harder to spot in dense tissue than in fatty tissue, because the tumor looks a lot like the tissue around it. An analogy is often used to describe the way cancer (dense) tissue looks on film, "It's like looking for a polar bear in a snow storm”.

Breast cancers are readily seen in fatty tissue with up to 98% sensitivity in film mammography. Breast density is one of the strongest--if not the strongest--predictors of mammography screening failure [7]. In a study of breast cancers that are missed by radiologists, Georgen et al.[8] found that missed cancers were significantly lower in density than detected cancers, and missed cancers were more often seen on only one of the two views.

B. Computer Aided Detection (CAD) – Current Practice

One method of helping radiologists screen mammograms for signs of cancer is prompting, in which computer based algorithms are used to detect potential abnormalities in digital images and to draw attention to the corresponding regions in the original films. Prompting aims to improve radiologists’ performance by reducing the number of false negative errors, *i.e.* cases in which a mammogram containing a significant abnormality is classified as normal. Researchers have been developing algorithms to detect mammographic abnormalities for the past 25 years.

While designing the computer based algorithms it is not always easy to determine the key characteristics that differentiate normal and abnormal mammographic appearances, as both show a high degree of variability. One method of dealing with this problem involves extracting information from a large training set of images chosen to represent the expected range of appearances. This information is used to produce statistical models that encapsulate the important features of the training data, and can be used to detect these features in previously unseen images. But when the data source changes then the underlying algorithms need to be changed as well. For example the algorithms developed for use with film digitizers would need to be modified to work with images produced by digital systems. Because the pixel size required by the main CAD systems are of the order of 50 µm, whereas many digital systems use a pixel size of 100 µm. The pixel size may be an important factor in the performance of the classification algorithms [9].

C.Prompting in Mammography

The goal of a CAD system is to reduce errors by drawing radiologists' attention to possible abnormalities. CAD is not intended to be used as a computer-aided diagnosis tool: the decision as to whether a feature is of clinical significance remains with the radiologist. In practice, however, the distinction between detection and diagnosis may be blurred. One study has indicated that, for subtle microcalcification clusters, subjects' confidence that a cluster was present was increased if the cluster was prompted, and decreased if the cluster was unprompted [10]. Another study reported that prompting can entail an increase in False Positive decisions without necessarily having an overall effect on confidence levels [11]. The first study would seem to indicate that radiologists' confidence with respect to the detection task is affected by prompting, but that their diagnostic decision making remains largely unaffected. The second study, however, raises doubts regarding the latter conclusion [12].

D.Computer Aided Detection (CAD) Using HCS

One of the capabilities of the human vision process when visualizing images is the ability to visualize them at different levels of details. HCS procedure has been developed to mimic this capability of human vision process. The developed HCS procedure automatically generates a hierarchy of segmented images. The hierarchy represents the continuous merging of similar, spatially adjacent or disjoint, regions as the allowable threshold value of dissimilarity between regions, for merging, is gradually increased [13].

Currently existing CAD processes yield a single solution which might not be the most appropriate for all the images the process is applied to. In contrast HCS process provides a hierarchical set of image segmentations which is a set of several image segmentations at different levels of segmentation details in which the segmentation at coarser levels of detail can be produced from simple merges of regions from segmentations at finer levels of details. Thus HCS gives the opportunity for the users to inspect the different segmentation results and help them to "see" abnormalities in the image which were not previously visible to the naked eye.

Currently existing CAD processes is designed by training the algorithm in an earlier set of mammograms image data set. The principal difficulty with the current prevalent approaches is ensuring that the number of examples is sufficient to represent adequately the variety of pathologies and normal appearances that could be encountered. Our HCS based CAD process avoids this difficulty by comparing and highlighting the dissimilarities within the same image.

Currently existing CAD process places prompts to alert readers to potential lesions. But our HCS based CAD process highlights the dissimilarity between the potentially diseased area and the healthy area.

E.Highlighting Dissimilarities in X-ray Mammograms using HCS

Fig. 6 shows the mammogram, mdb102, from the mini-MIAS database of mammograms [14]. It has a dense-glandular background tissue with a abnormality of malignant asymmetric density (circled in white).

A region of interest (ROI) of size 100x174 (shown in white in Fig. 6) was chosen enclosing the abnormality. The HCS process was done within the ROI. Fig. 7 and Fig. 8 illustrate the results of HCS applied to mdb102 mammogram image data, within the ROI.

The number of regions will decrease as the allowable dissimilarity level between the merging regions is increased. Because, as the allowable dissimilarity between the merging regions is increased more and more regions having higher dissimilarity, than the earlier merged regions, will merge. Table I lists the number of regions for each of the segmentation in the hierarchy and the corresponding dissimilarity between the regions. Table II and Table III give the properties of the different regions for each of the segmentation in the hierarchy.

From the results of segmentation of the mammogram image data (mdb102) illustrated in Fig. 7 and Fig. 8 the following general observations could be made :

1) The number of regions decrease as the allowable dissimilarity level between the merging regions is increased.
   As the allowable dissimilarity between the merging regions is increased more and more regions having higher dissimilarity, than the earlier merged regions, merge and the homogeneity within the regions decrease. This can be observed by the increase in the standard deviation of the density values within the merged regions.
2) The proposed HCS based CAD system, unlike the currently existing CAD systems, does not try to detect and prompt the abnormal regions. Instead the designed HCS process strives to highlight the subtle differences within the same image by outlining those parts of the image having similar properties, for a given allowable dissimilarity level between the regions.
   The outlining of the similar part of the regions within the image might be able to draw the attention of the expert to parts of the image which are dissimilar and hence having the possibility of diseased.

VI. Conclusion

This paper has discussed the possibility of using HCS as a perceptual aid to assist radiologists. We have shown how the HCS process could possibly be used, to reduce errors, by drawing the attention of the radiologists to areas of dissimilarity within an image.

This is a very preliminary work albeit promising. Extensive user level testing need to be done to conclusively demonstrate the usefulness of HCS as a probable CAD tool.

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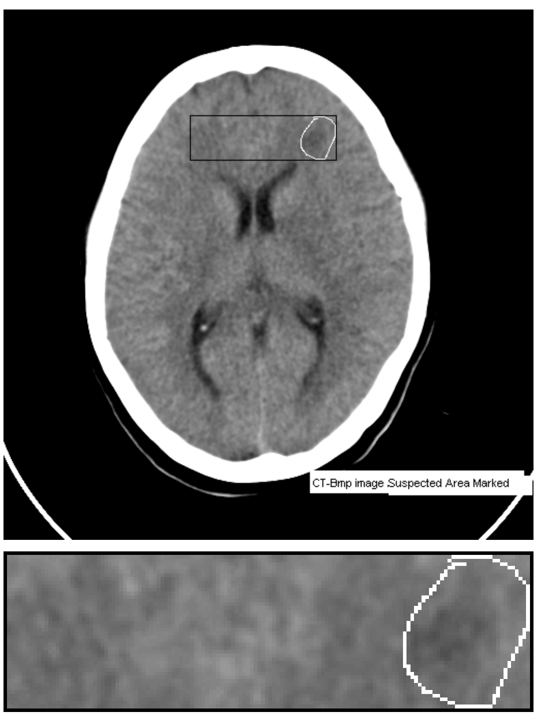

Fig. 3. CT image showing the suspected area outlined in white by a neuroradiologist.

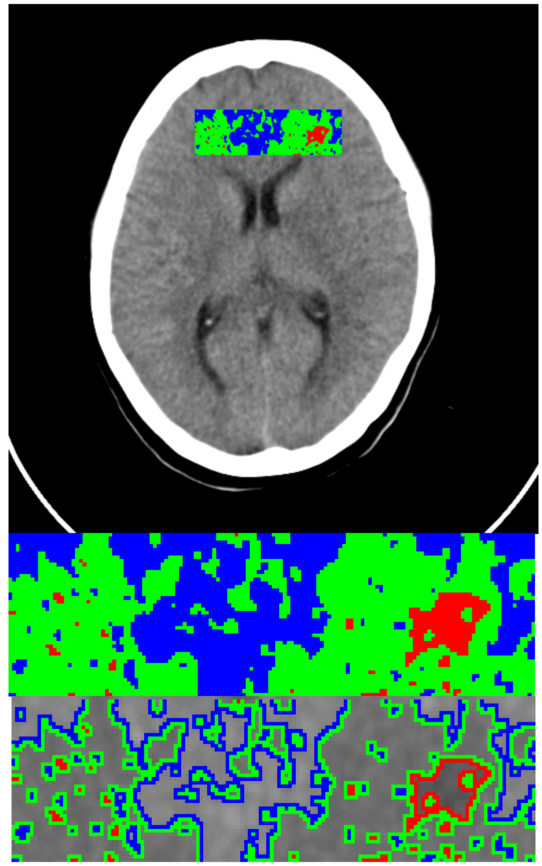

Fig. 4. Segmentation of the Grey matter, White matter and Stroke affected regions and their boundaries by HSEG [6].

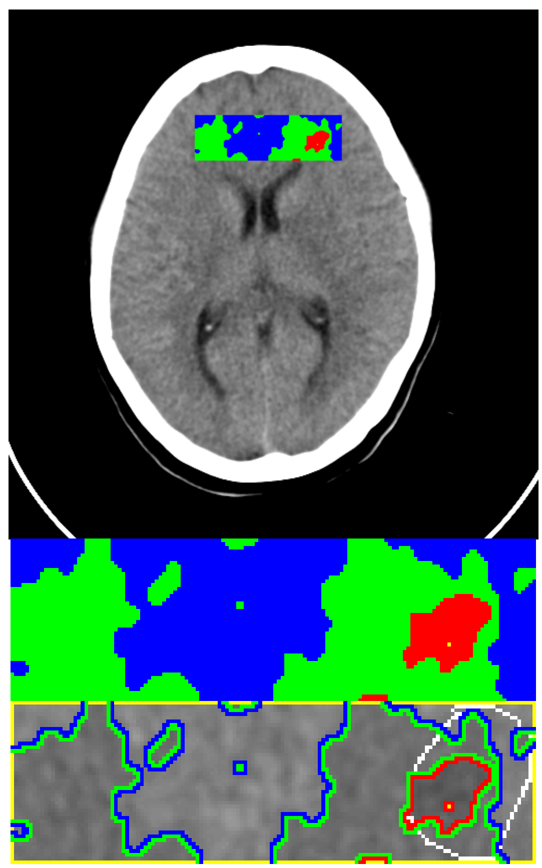

Fig. 5. Segmentation of the Grey matter, White matter and Stroke affected regions and their boundaries by our HCS [3].

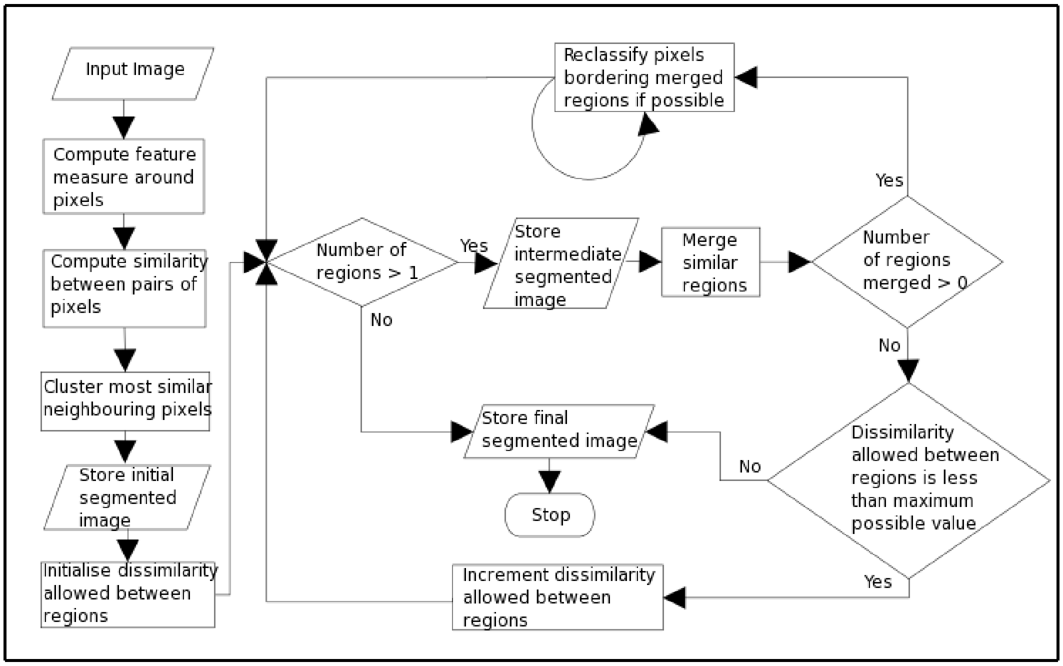

Fig. 1. Flow chart illustrating the different operations within the Hierarchical Clustering based Segmentation (HCS) process.

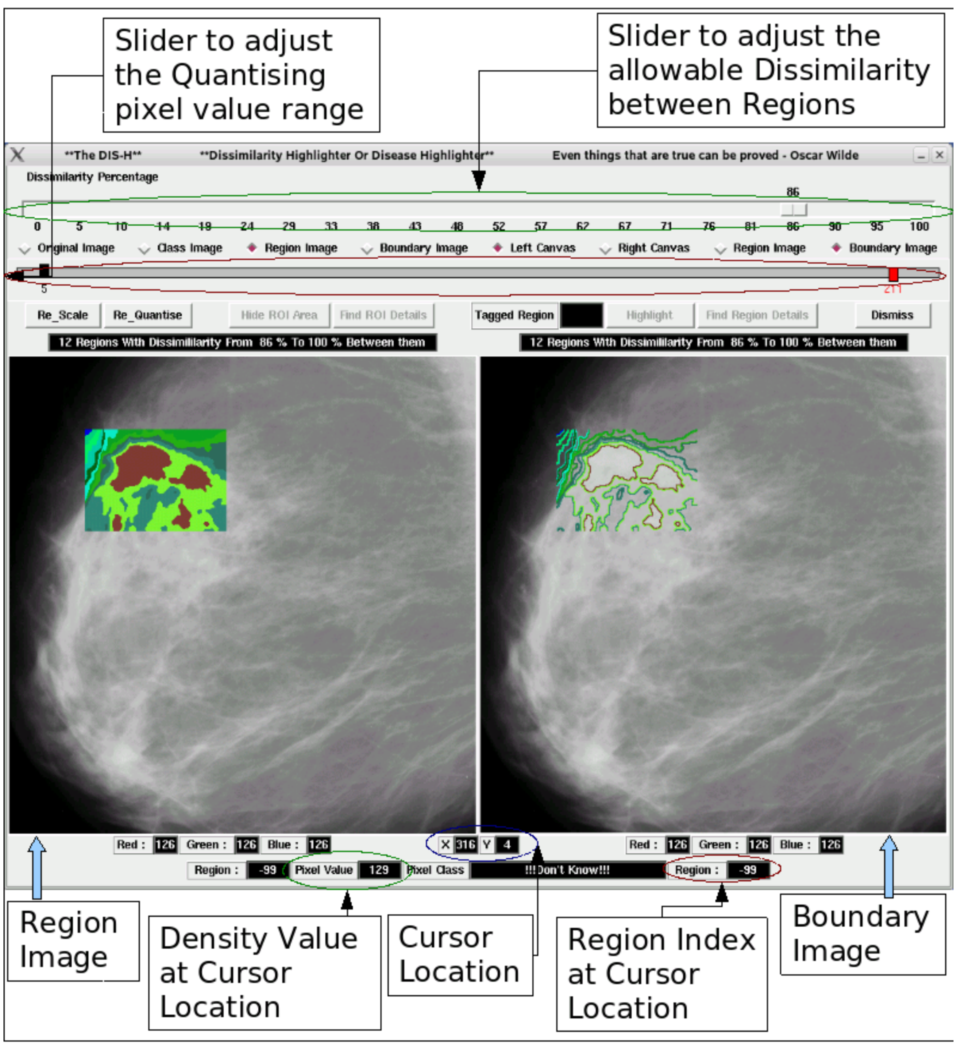

Fig. 2. Annotated screen shot of the GUI. GUI used to visualize the output of the Hierarchical Clustering based Segmentation (HCS)

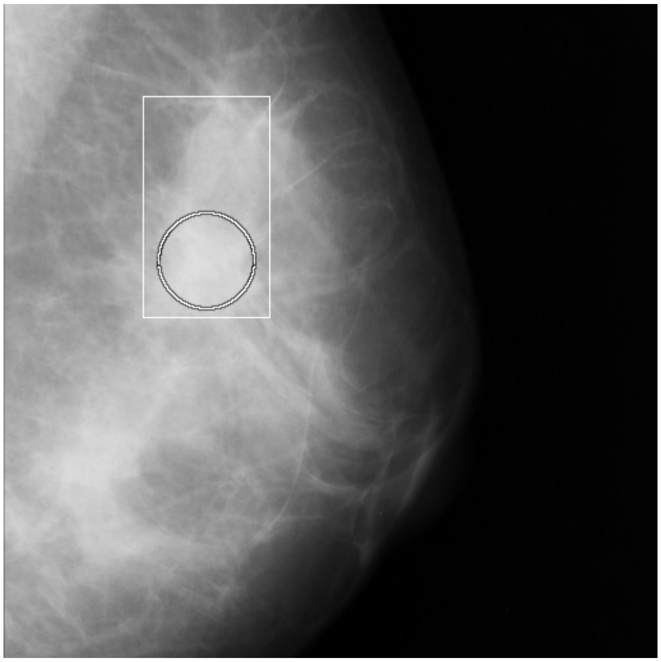

Fig. 6. Digitised X-ray Mammogram image data mdb102 [14], having dense glandular background tissue with malignant asymmetric density. Abnormal part of the image circled, in white; based on an expert findings.

TABLE I
Details of the Segmented Regions Shown in Fig. 7 to Fig. 10

Segmented Image	Number of Regions	Dissimilarity between the Regions
Fig. 7	6	> 24%
Fig. 8	4	> 31%

TABLE II
Details of the Six Regions in the Intermediate Segmentation Result Shown in Fig. 7.

Region Color	Pixel Value	Within the	Segmented	Regions
	Minimum	Maximum	Average	STD
Red	200	224	212	5.1
Fuschia	184	206	196	4.3
Yellow	171	192	182	4.2
Blue	154	178	169	4.4
Aqua	143	166	153	4.5
Green	132	150	141	3.3

TABLE III
Details of the Four Regions in the Intermediate Segmentation Result Shown in Fig. 8.

Region Color	Pixel Value	Within the	Segmented	Regions
	Minimum	Maximum	Average	STD
Red	200	224	211	5.4
Fuschia	178	206	194	5.5
Blue	154	190	174	6.1
Green	132	166	147	7.5

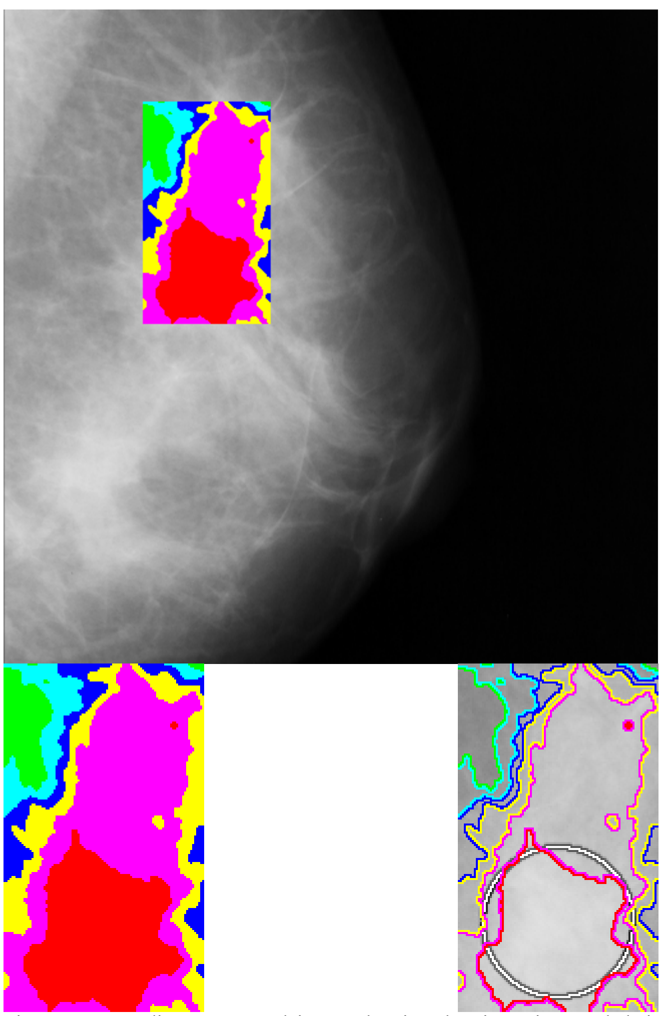

Fig. 7. Intermediate segmented image showing the six regions and their boundaries.

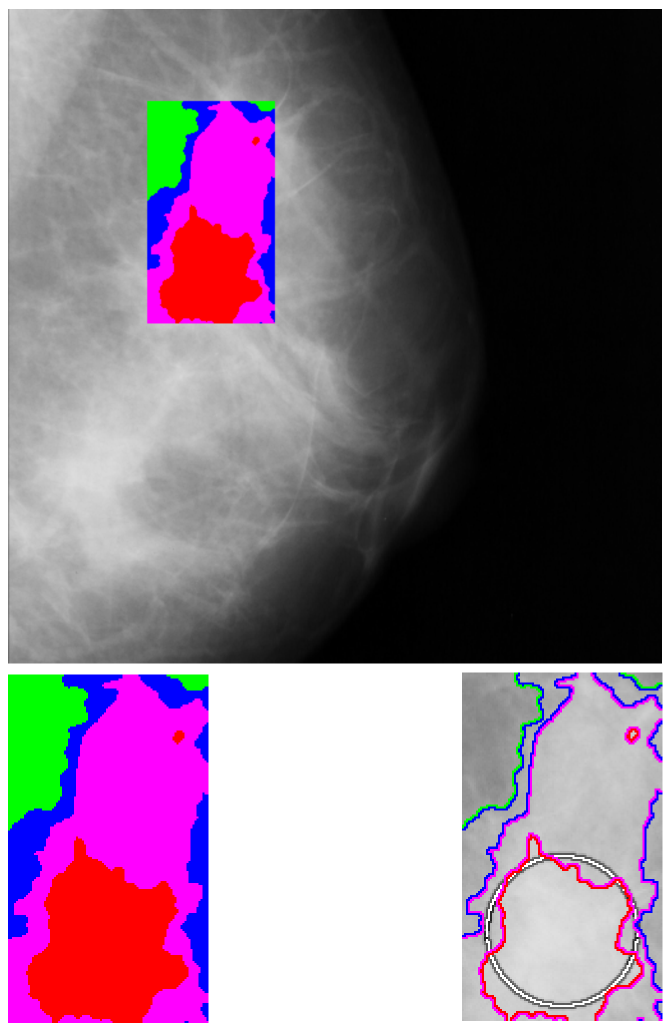

Fig. 8. Intermediate segmented image showing the four regions and their boundaries.