EDGE DETECTION AND SEGMENTATION OF HEART IMAGE

Patel Janakkumar Baldevbhai*

R.S. Anand**

Abstract—

This Paper presents various edge detection methods and segmentation methods. All methods are applied on heart image. All methods and their results are evaluated through standard assessment parameters. Edge Detection Methods like Sobel, Prewitt, Robert, Log, Zero Crossing, and Canny are compared with Proposed Method of Marker based Watershed Segmentation Technique for color image segmentation. Various standard assessment parameters are PSNR, NCC, AD, SC, NAE, STD, COV, UIQI, CC, SSI and DSI. Result Tables and Graphs clearly shows that proposed method gives better results as compared to edge detection methods.

Index Terms— Edge Detection, Gradient, Image Segmentation, Watershed Transform, Marker based Watershed Segmentation Technique

* Image & Signal Processing Group, Electrical Engineering Department, Research Scholar, EED, Indian Institute of Technology Roorkee, Uttarakhand, India,Pin:247 667.

** Electrical Engineering Department, Professor, EED, Indian Institute of Technology Roorkee, Uttarakhand, India.

1. Introduction

In computer vision, **segmentation** refers to the process of partitioning a digital image into multiple segments (sets of pixels) (Also known as super pixels) [1-4]. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze [5]. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Image segmentation is a key step for image processing, pattern recognition, computer vision. Many existing methods for image description, classification, and recognition highly depend on the segmentation results. The popular approaches for image segmentation are edge-based methods [1], and watershed methods.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Segmentation subdivides an image into it's constitute regions or objects. The level to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects of interests in an application have been isolated. Image segmentation algorithms generally are based on one of two basic properties of intensity values: discontinuity and similarity.Image segmentation is very essential and critical to image processing and pattern recognition.

2. Edge Detection

A point is being an edge point if its two—dimensional first-order derivative is greater than a specified threshold. A set of such points that are connected according to a predefined criterion of connectedness is by definition an ***edge***. In practice, optics, sampling and other image acquisition. Imperfections yield edges that are blurred. The slope of the ramp is inversely proportional to the degree of blurring in the edge. The "thickness" of edge is determined by the length of the ramp.

First-order derivatives of a digital image are based on various approximations of the 2-D gradient. Second-order derivative is defined as digital approximations to the Laplacian of a 2-D function. *Conclusion*: The first derivative can be used to detect the presence of an edge at a point in an image. Similarly, the sign of the second derivative can be used to determine whether an edge pixel lies on the dark or light side of an edge (*zero -crossing*). *Problem*: Derivatives are sensitive to noise. Function that provides edge detection in Matlab is edge BW = edge(I, method'). Supported methods of edge detection are gradient magnitude methods Sobel, Prewitt, Roberts; next zero crossings, Laplacian and Canny method. The Canny method applies two thresholds to the gradient: a high threshold for low edge sensitivity and a low threshold for high edge sensitivity.

2.1 Edges Linking and Boundary Detection:

Edge detection algorithms typically are followed by linking procedures to assemble edge pixels into Meaningful edges. (for example, breaks caused by noise.)

2.2 Local Processing

Criteria: the strength of the response of the gradient operator / the direction of the gradient vector A point in the predefined neighborhood is linked to the pixel if both magnitude and direction criteria are satisfied.

2.3 Edge detection

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. Edge detection is highly useful in many applications including image segmentation, pattern recognition. Edge detection is one of the fundamental approaches in digital image processing.The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries.

Most common differentiation operator is the gradient.

$$\nabla f(x,y) = \begin{bmatrix} \dfrac{\partial f(x,y)}{\partial x} \\ \dfrac{\partial f(x,y)}{\partial y} \end{bmatrix}$$

The magnitude of the gradient is:

$$|\nabla f(x,y)| = \left(\left(\frac{\partial f(x,y)}{\partial x} \right)^2 + \left(\frac{\partial f(x,y)}{\partial y} \right)^2 \right)^{1/2}$$

The direction of the gradient is given by:

$$\angle \nabla f(x,y) = \tan^{-1}\left(\frac{\partial f}{\partial y} \Big/ \frac{\partial f}{\partial x} \right)$$

2.4 A simple edge model

Although certain literature has considered the detection of ideal step edges, the edges obtained from natural images are usually not at all ideal step edges. Instead they are normally affected by one or several of the following effects:

- Focal blur caused by a finite depth-of-field and finite point spread function.
- Penumbral blur caused by shadows created by light sources of non-zero radius.
- Shading at a smooth object edge.
- Local secularities or interreflections in the vicinity of object edges.

Although the following model does not capture the full variability of real-life edges, the errorfunctionerf has been used by a number of researchers as the simplest extension of the ideal step edge model for modeling the effects of edge blur in practical applications (Zhang and Bergholm 1997, Lindeberg 1998). Thus, a one-dimensional image *f* which has exactly one edge placed at $x = 0$ may be modeled as:

At the left side of the edge, the intensity is, and right of the edge it is. The scale parameter σ is called the blur scale of the edge.

2.5 Approaches to edge detection

There are many methods for edge detection, but most of them can be grouped into two categories, search-based and zero-crossing based. The search-based methods detect edges by first computing a measure of edge strength, usually a first-order derivative expression such as the gradient magnitude, and then searching for local directional maxima of the gradient magnitude using a computed estimate of the local orientation of the edge, usually the gradient direction. The zero-crossing based methods search for zero crossings in a second-order derivative expression computed from the image in order to find edges, usually the zero-crossings of the Laplacian or the zero-crossings of a non-linear differential expression. As a pre-processing step to edge detection, a smoothing stage, typically Gaussian smoothing, is almost always applied. The edge detection methods that have been published mainly differ in the types of smoothing filters that are applied and the way the measures of edge strength are computed. As many edge detection methods rely on the computation of image gradients, they also differ in the types of filters used for computing gradient estimates in the x- and y-directions.

2.6 Edge element extraction

[1] High-emphasis spatial frequency filtering. Since high spatial frequencies are associated with sharp changes in intensity, so one can enhance or extract edges by performing high-pass filtering : i.e. take the Fourier transform of the picture, say F(*f*(x,y))=F(u,v) where *f*(x,y) and F(u,v) are the original gray level function and its Fourier transform respectively. F is the Fourier operator. Multiply F by the linear spatial filter H: E(u,v) = F(u,v).H(u,v) and take the inverse transform e(x,y) = F^{-1}(E(u,v)) where e(x,y), is the filtered picture of f(x,y) and E(u,v) its Fourier transform and F^{-1} is the inverse Fourier transform operator.

[2] Gradient operators. The gradient operator is defined as [1]

$$\nabla f(x,y) = \frac{\partial f}{\partial x} i + \frac{\partial f}{\partial y} j$$

Where

$$|\nabla f(x,y)| = \left(\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right)^{\frac{1}{2}}$$

and the direction of $\nabla f(x, y)$ is

$$\tan^{-1}\frac{\left(\frac{\partial f}{\partial y}\right)}{\left(\frac{\partial f}{\partial x}\right)}$$

Where f is the original gray level function; i and j are unit vectors in the positive x and y directions respectively. Roberts' cross operator is based on a 2 x 2 window

$$g(i,j) = [\ (f(i,j) - f(i+1,j+1))^2 + (f(i+1,j) - f(i,j+1))^2\ ]$$

Where$f$ (i, j) and g (i, j) are the gray level function and magnitude of gradient of point (i, j) respectively.

3. Edge based Segmentation

Edge-based segmentation techniques use nonuniform measurements or discontinuities in the image function for the division of an image into regions. Local and global techniques can be distinguished from one another in principle. Local techniques use only the information in a pixel's local neighborhood for the detection of an edge pixel. In contrast, global techniques implement a type of global optimization for the entire image and thus identify an edge pixel only after several optimizations for the entire image and thus identify an edge pixel only after several Optimization steps and changes in large areas of the image. Most previously known global techniques for color image segmentation use differing types of Markov random fields, Common to them are computationally costly optimization techniques and long processing times. Here a limitation on local techniques results from reasons of practicability.

3.1Local Techniques

In addition to vector-valued formulas, monochromatic-based formulas are also common for the detection of edges in color images in edge-based segmentation of color images.

Lanser [6] proposed a color image segmentation that initially detects edges separately in the vector components in the CIELAB color space and subsequently unites the group of the resulting edge pixels. For segmentation it is crucial that closed contours are detected, or that only small gaps in the contours are to be closed. For this Lanser uses the intersection of the edge pixels.

The transition from detected contours to regions results from complement formation. By means of a morphological opening, Lanser opens small dividers between two regions in order to merge similar regions. The remaining holes in the regions are expanded in conclusion by a controlled region-growing technique.

3.2 Canny edge detection

Canny (1986) considered the mathematical problem of deriving an optimal smoothing filter given the criteria of detection, localization and minimizing multiple responses to a single edge. He showed that the optimal filter given these assumptions is a sum of four exponential terms. He also showed that this filter can be well approximated by first-order derivatives of Gaussians. Canny also introduced the notion of non-maximum suppression, which means that given the pre-smoothing filters, edge points are defined as points where the gradient magnitude assumes a local maximum in the gradient direction.

Although his work was done in the early days of computer vision, the Canny edge detector (including its variations) is still a state-of-the-art edge detector. Unless the preconditions are particularly suitable, it is hard to find an edge detector that performs significantly better than the canny edge detector.The Canny-Deriche detector (Deriche 1987) was derived from similar mathematical criteria as the Canny edge detector, although starting from a discrete viewpoint and then leading to a set of recursive filters for image smoothing instead of exponential filters or Gaussian filters.The differential edge detector described below can be seen as a reformulation of Canny's method from the viewpoint of differential invariants computed from a scale-space representation.

3.3Second-order approaches to edge detection

Some edge-detection operators are instead based upon second-order derivatives of the intensity. This essentially captures the rate of change in the intensity gradient. Thus, in the ideal continuous case, detection of zero-crossings in the second derivative captures local maxima in the gradient.The early Marr-Hildreth operator is based on the detection of zero-crossings of the Laplacian operator applied to a Gaussian-smoothed image. It can be shown, however, that this operator will also return false edges corresponding to local minima of the gradient magnitude. Moreover, this operator will give poor localization at curved edges.

The Laplacian of a two-dimensional function $f(x, y)$ is given by

$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}$$

This can be implemented using the following mask:

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \qquad \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

A discrete approximation can be obtained as:

Z_1	Z_2	Z_3
Z_4	Z_5	Z_6
Z_7	Z_8	Z_9

$$\nabla^2 f = 4z_5 - (z_2 + z_4 + z_6 + z_8)$$

The Laplacian is rotation invariant!

$$\nabla^2 f = 8z_5 - (z_1 + z_2 + z_3 + z_4 + z_6 + z_7 + z_8 + z_9)$$

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

The Laplacian operator suffers from the following drawbacks:

(1) It is a second derivative operator and is therefore extremely sensitive to noise.

(2) Laplacian produces double edges and cannot detect edge direction.

· It is particularly useful when the gray-level transition at the edge is not abrupt but gradual.

4.Image Segmentation using Watershed Transform

Segmentation by watersheds embodies many of the concepts of the other three approaches and, as such, often produces more stable segmentation results, including continuous segmentation boundaries.

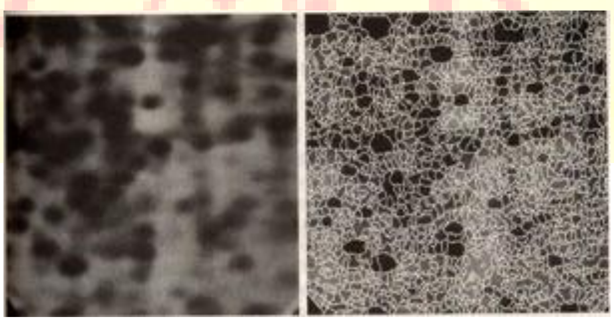
4.1Basic Concepts

The concept of watersheds is based on visualizing an image in three dimensions: two spatial coordinates versus gray levels.The Watershed method, also called the watershed transform, is an image segmentation approach based on gray-scale mathematical morphology, to the case of color or, more generally speaking, multi component images.

4.2 The Use of Markers

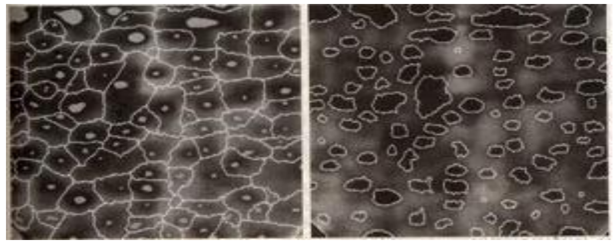
In a conventional watershed algorithm there is a problem of over segmentation. So markers are used to overcome this problem.

A *marker* is a connected component belonging to an image.



(a) *(b)*

Figure 1*(a) Electrophoresis image (b) Result of applying the conventional watershed segmentation [1][2] algorithm to the gradient image. Over segmentation is evident.*



(a) ***(b)***

Figure2*(a) Image showing internal markers (light gray region) and external markers (watershed lines) (b) Result of segmentation [1][2]*

4.3 Segmentation by watershed transformation

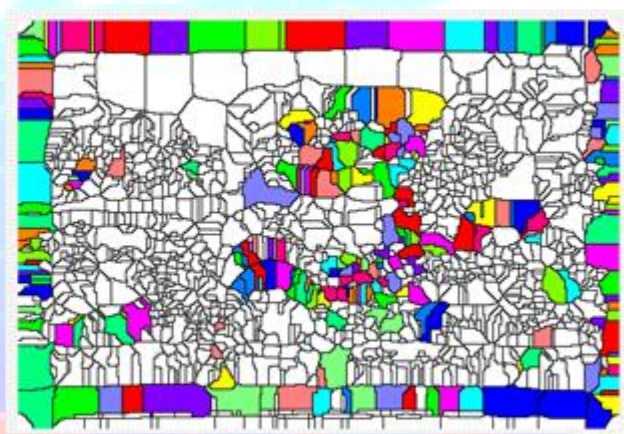


Figure 3 *Watershed Segmentation*

Segmentation by watershed transformation can be seen as a region-growing technique. Watershed transformation forms the basis of a morphological segmentation of gray-level images. It was developed by Meyer and Beucher [7] and converted by Vincent and Soille [9] into a digital algorithm for gray-level images. The technique can be applied to the original image data or to gradient images. In the latter case it is based on the discontinuities of image function and for this reason it is indirectly a type of edge –based technique.Arnau Oliver et al. [8] presented a paper in 2010. The aim of their paper is to review existing approaches to the automatic detection and segmentation of masses in mammographic images, highlighting the key-points and main differences between the used strategies. The key objective is to point out the advantages and disadvantages of the various approaches. In future prospect Luc Vincent and Pierre Soille [9] suggested that it is expected to contribute to new insights into the use of watersheds in the field of image analysis.The watershed transform is a mathematical morphological approach to image segmentation (Beucher and Lenteuejoul, 1979; Vincent and Soille, 1991). Its name stems from the manner in which the algorithm segments the image regions into catchment basins (the low points in intensity). If water falls into these basins, the level in each basin rises until it is shared with its neighbouring basin. Thus, the output of this algorithm is a hierarchy of basins. What remains is to select the most discriminative level of basins for each purpose.

Good segmentation results have been achieved for medical gray-level images as well as color images with the watershed transformation. For this reason the watershed transformation is presented here.

Before its use on color images is explained, the principle should be first clarified by gray-level image segmentation. If a gray-level image is viewed as a topographical relief, then the image value **E(p)** denotes the height of the surface area at position **p**. A path P of length ***l*** between two pixels **p** and **q** is a l+1-tupel ($\mathbf{p}_0,\mathbf{p}_1,\ldots,\mathbf{p}_{l-1},\mathbf{p}_l$) with $\mathbf{p}_0=\mathbf{p}$, $\mathbf{p}_l=\mathbf{q}$, and $(\mathbf{p}_i,\mathbf{p}_{i+1}) \epsilon$ G for all $i\epsilon[0,l)$. *G* denotes here the basis grid. A set M of pixels is called connected if for each pair of pixels **p,q**ϵ M a path exists between **p** and **q**, which only passes through pixels from M.

4.4 Watershed transformation

The watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minimum (LIM). Pixels draining to a common minimum form a catch basin, which represents a segment.

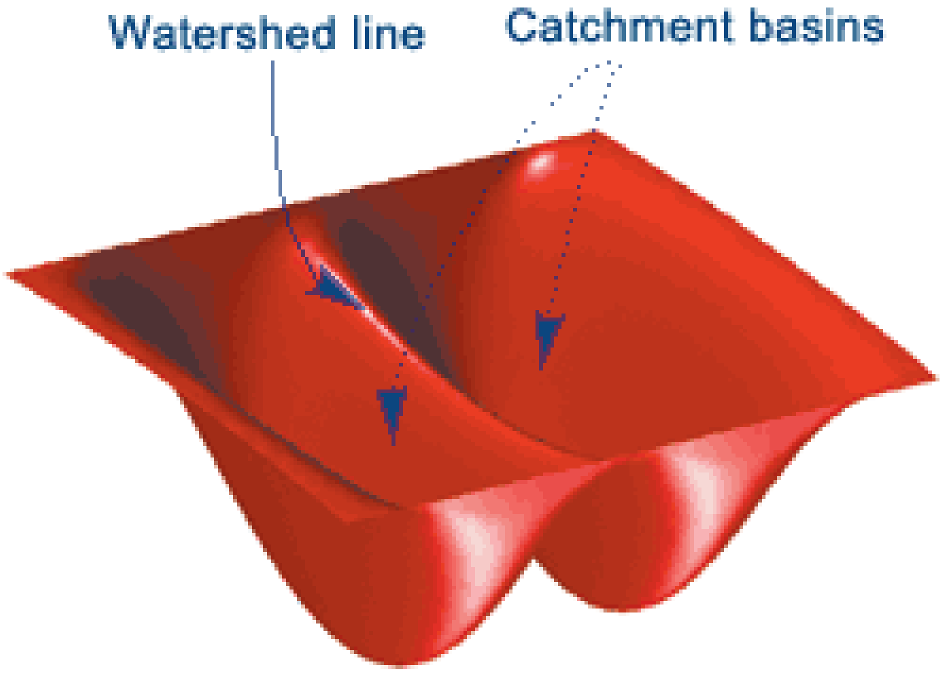


Figure 4*Watershed catchment basins*

The catchment basins provide a segmentation of the image, and the watershed boundaries define divisions**.**The watershed algorithm is a morphological algorithm that gives a partition of an image into catchment basins where every local minimum of the image belongs to one basin and where the basins' boundaries (the so-called watersheds) are located on the "crest" values of the image.

Using the watershed algorithm as a classifier was first suggested by Soille in [9]. Actually, in the inverted 3-D histogram of a color image, the clusters' cores *are* local minima. However, the watershed algorithm leads to an over partitioning of the color space due to the presence of non-significant local minima.

4.5 Proposed Marker based Watershed Segmentation Algorithm

The proposed Marker based watershed segmentation follows this basic procedure:

1] Compute a segmentation function. This is an image whose dark regions are the objects we are trying to segment.

2] Compute foreground markers. These are connected blobs of pixels within each of the objects.

3] Compute background markers. These are pixels that are not part of any object.

4] Modify the segmentation function so that it only has minima at the foreground and background marker locations.

5] Compute the watershed transform of the modified segmentation function. Finally the W.T. was applied to the gradient image of the original image using the markers obtained in the previous steps. It is not possible to obtain this result with other conventional methods of image segmentation.

5. Results and Discussion

5.1 Results of Edge Detection Method

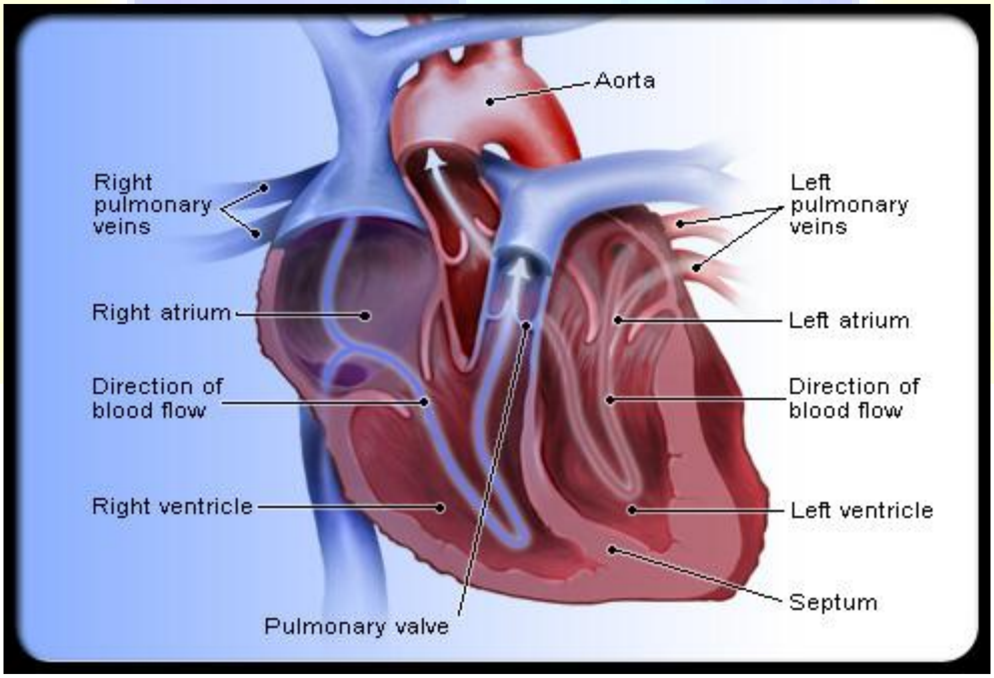
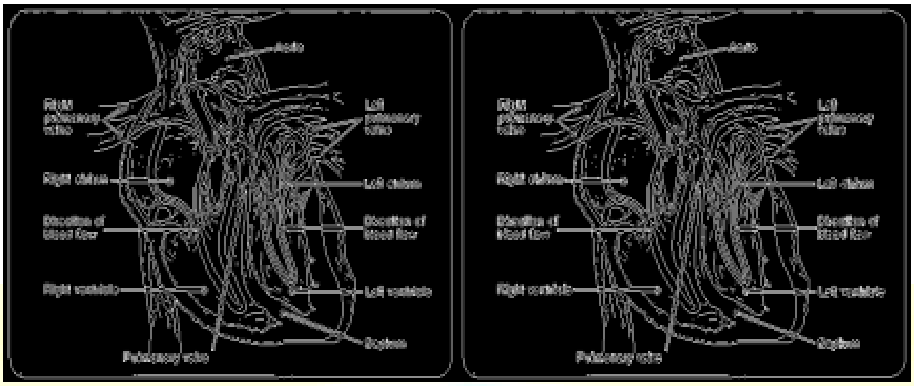
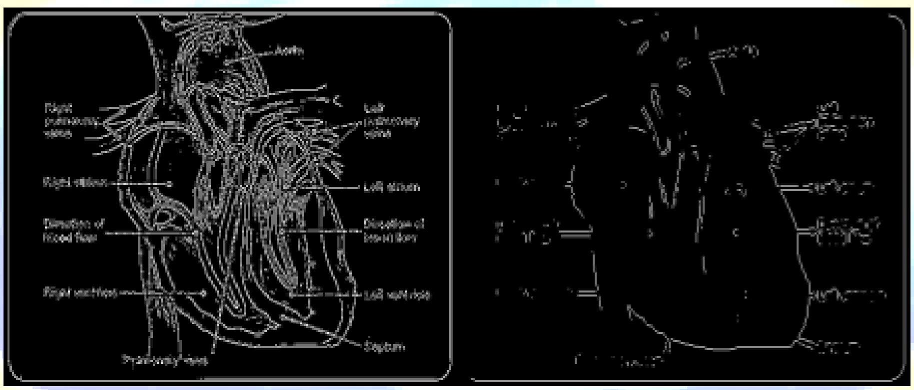


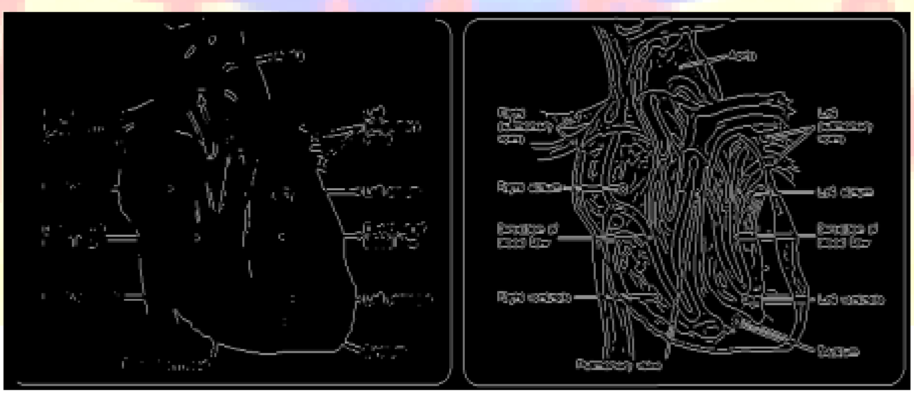
Figure 5 *Original heart image*



(a) **(b)**



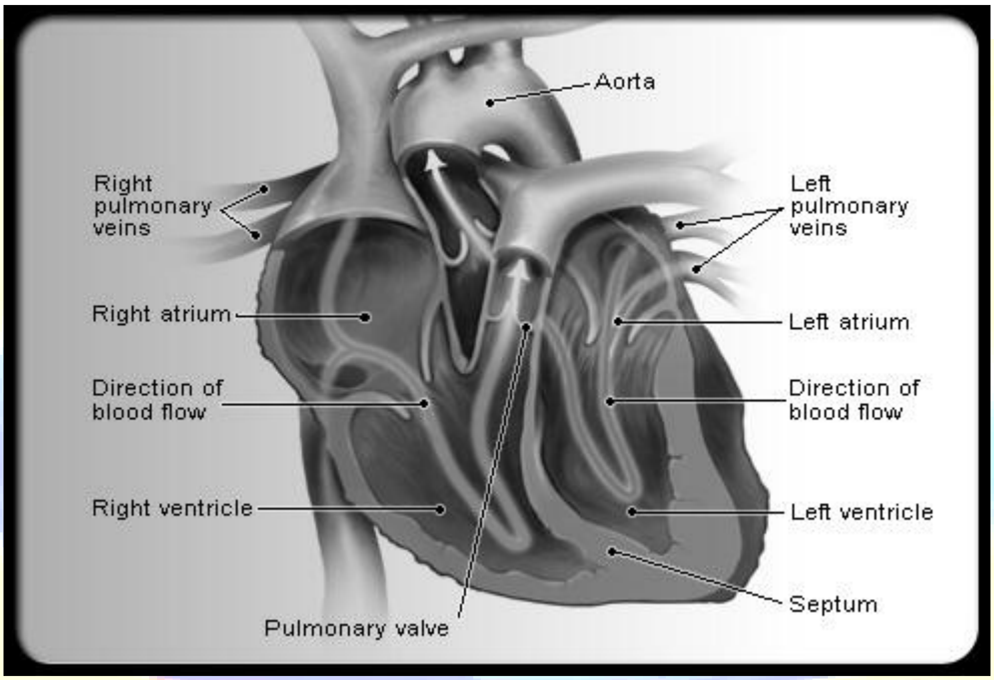
(c) **(d)**



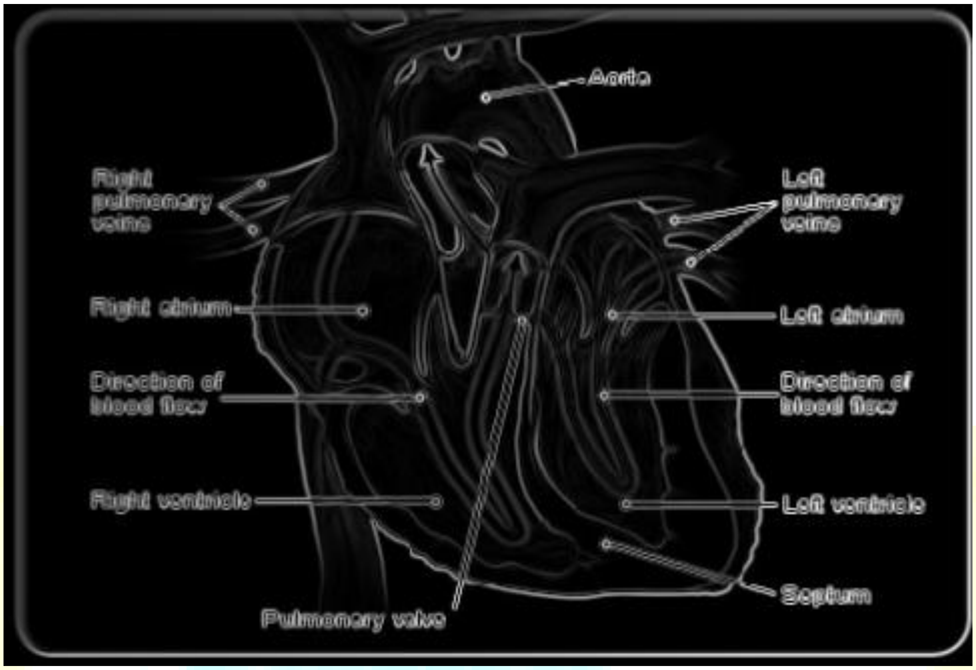
(e) **(f)**

Figure 6*Edge –detection with 0.020 threshold: (a) Sobel Operator (b) Prewitt Operator (c) Roberts operator (d) Log operator (e) Zero Crossing (f) Canny Method*

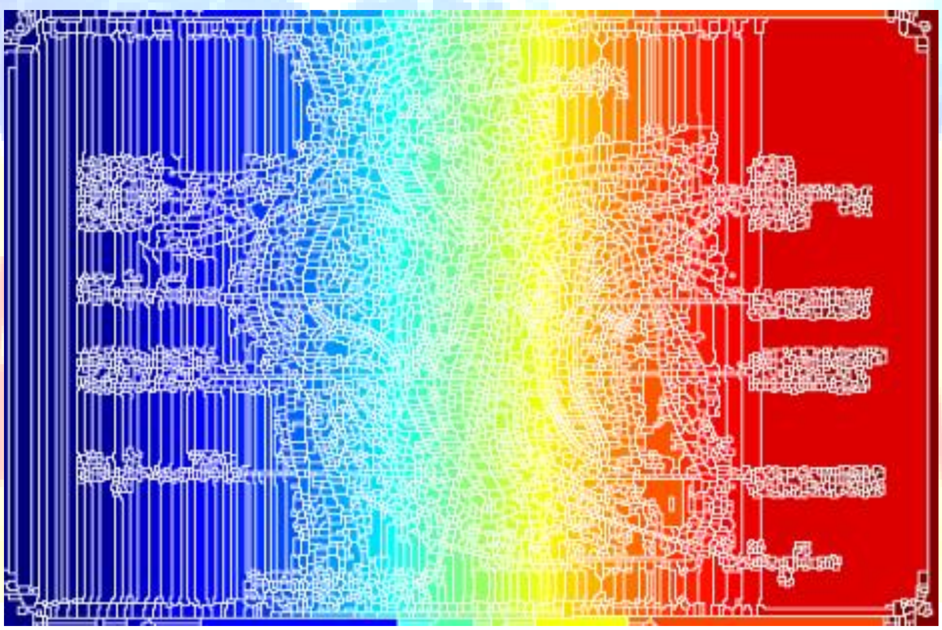
5.2 Results of Proposed Marker Controlled Watershed Segmentation Algorithm



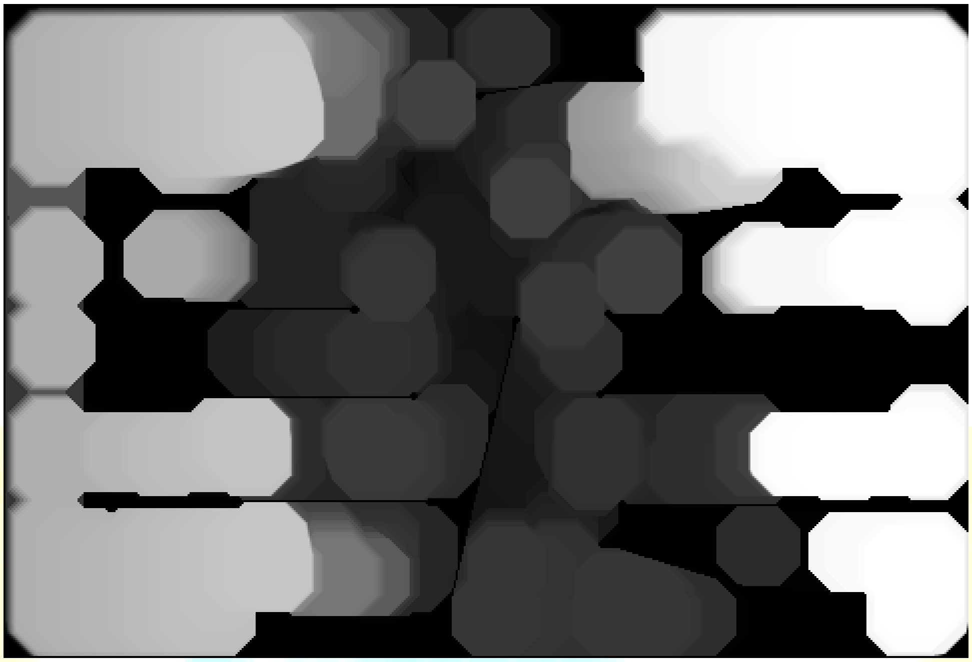
(a)



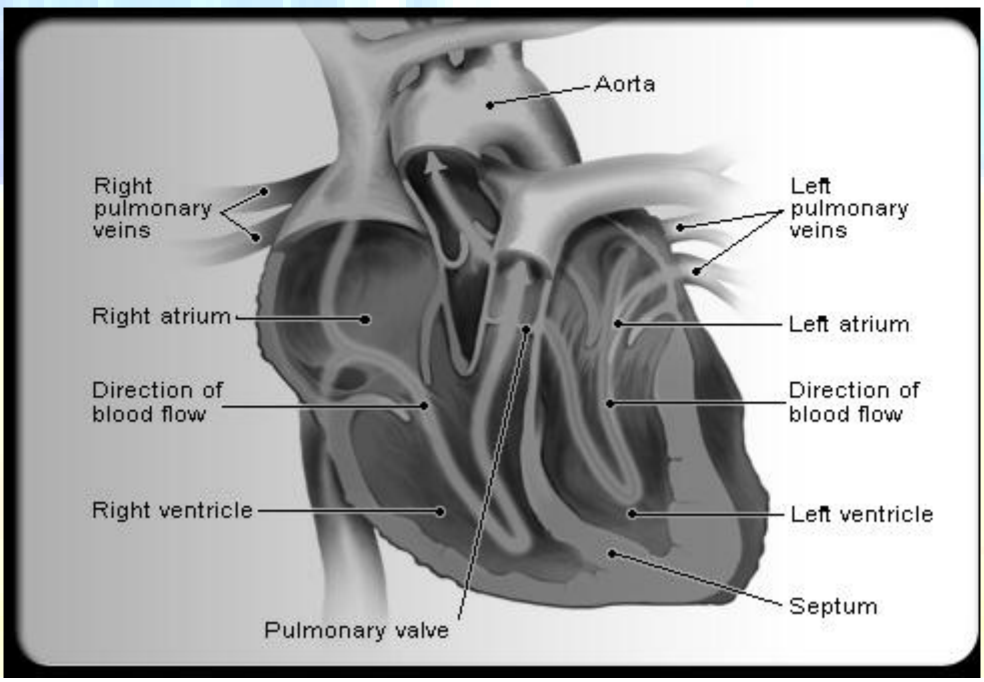
(b)



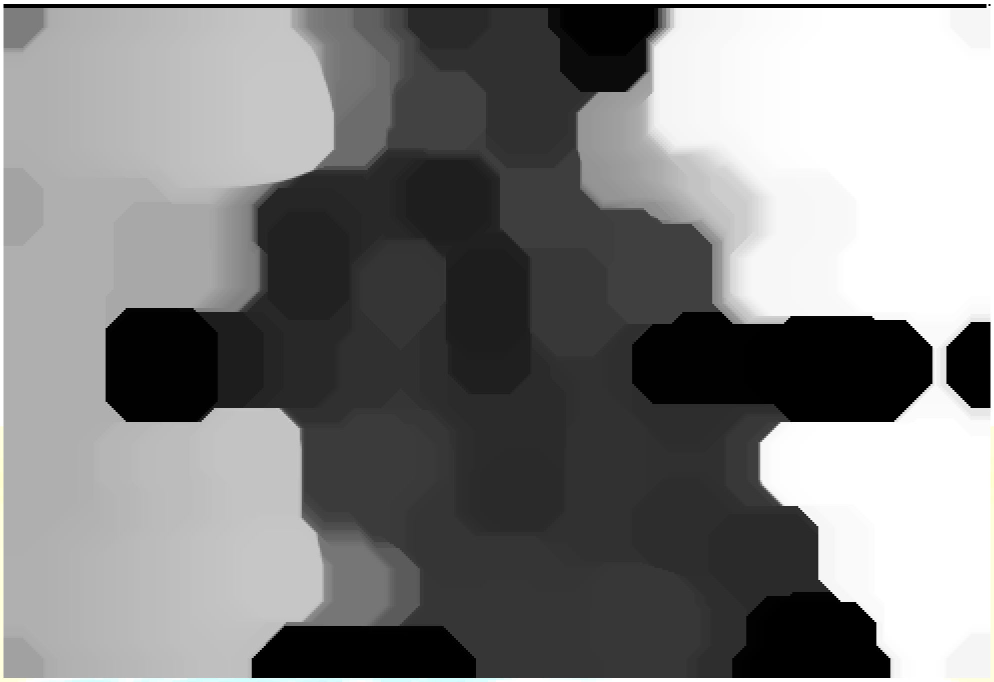
(c) *Proposed Watershed transform of gradient magnitude of heart*



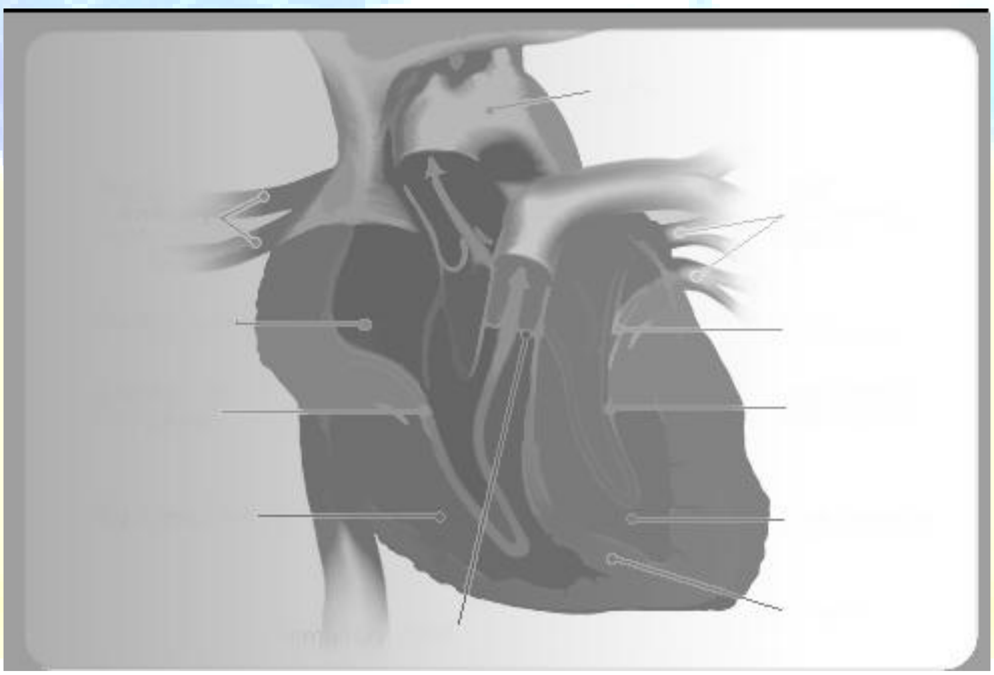
(d)


Aorta
Right pulmonary veins
Left pulmonary veins
Right atrium
Left atrium
Direction of blood flow
Direction of blood flow
Right ventricle
Left ventricle
Septum
Pulmonary valve

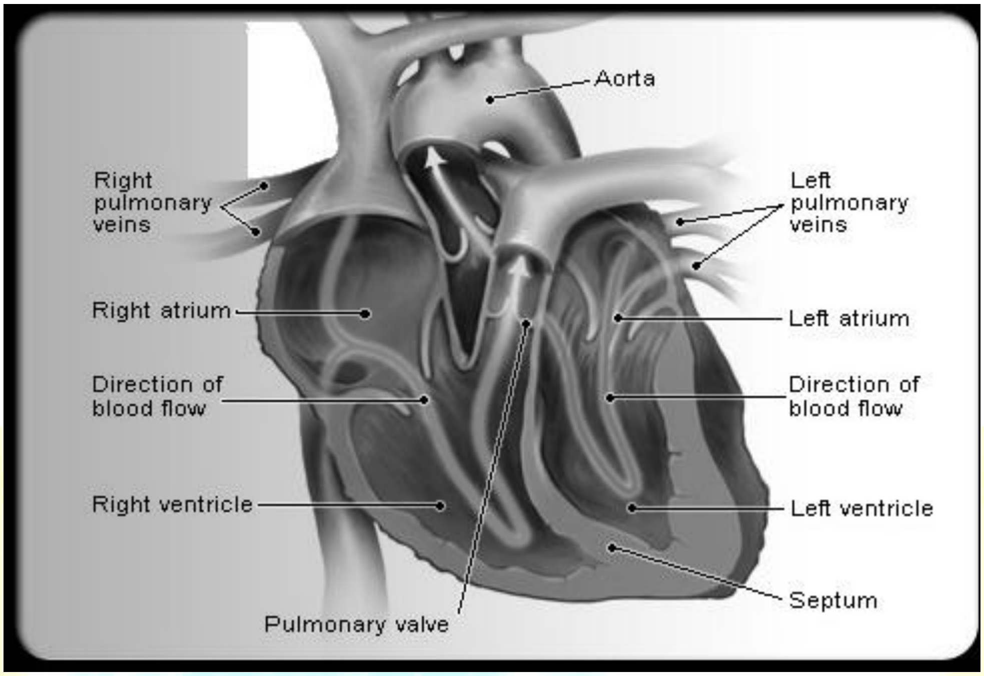
(e)



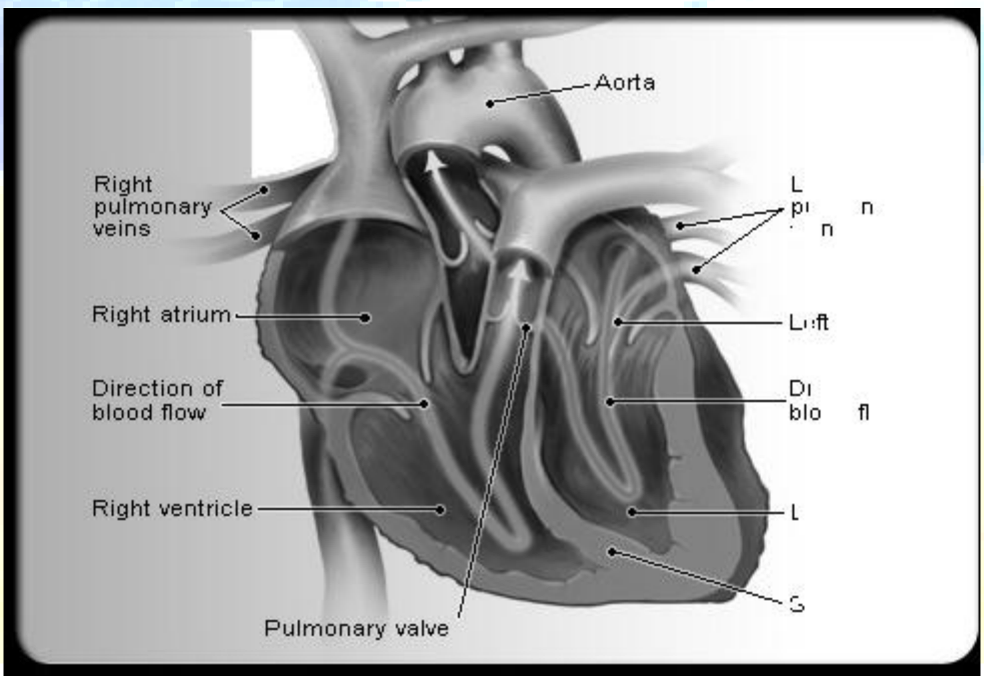
(f)



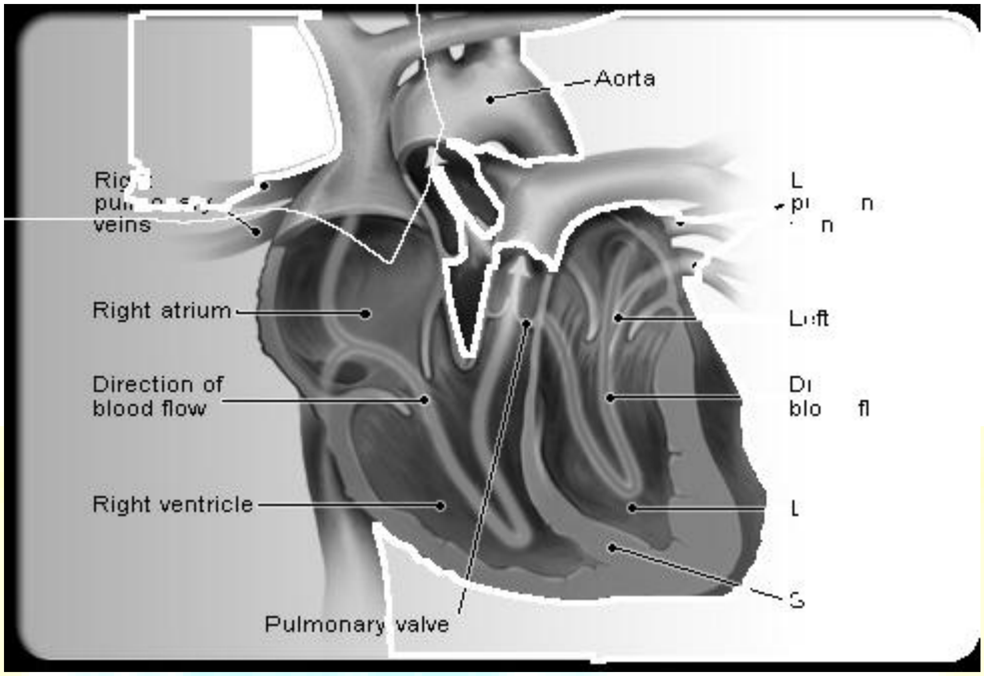
(g)


Aorta
Right pulmonary veins
Left pulmonary veins
Right atrium
Left atrium
Direction of blood flow
Direction of blood flow
Right ventricle
Left ventricle
Septum
Pulmonary valve

(h)

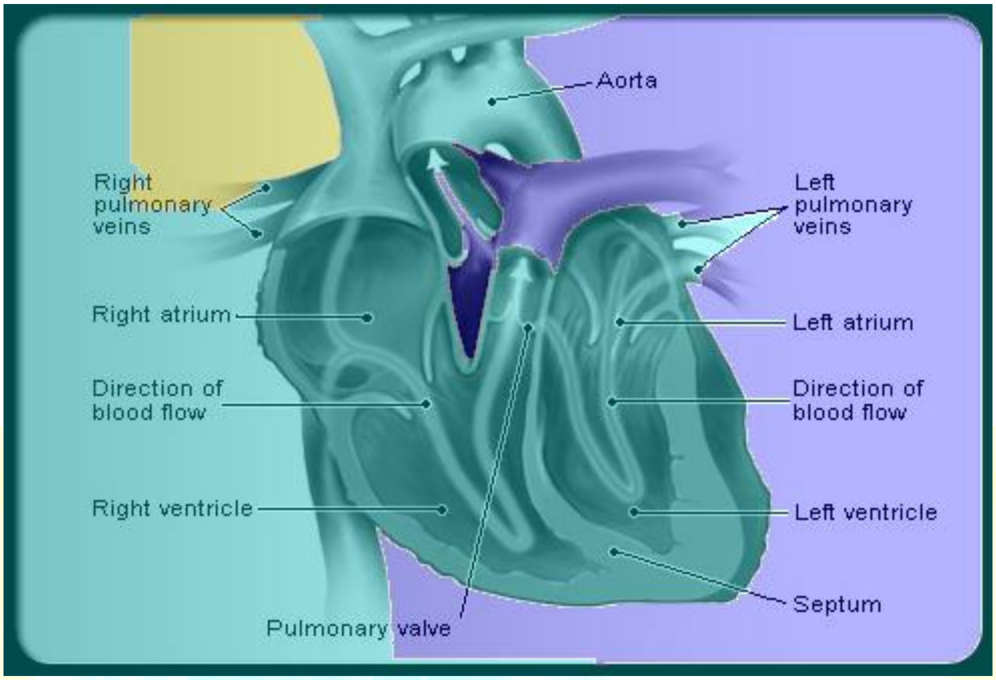

Aorta
Right pulmonary veins
Right atrium
Direction of blood flow
Right ventricle
Pulmonary valve

(i)


Aorta
Right atrium
Direction of
blood flow
Right ventricle
Pulmonary valve
Left

(j)

(k)



(l)

Figure 7*Results of Proposed segmentation techniques (a) Original image converted into grey image (b) gradient magnitude of the original image of heart(c) proposed watershed transform of gradient magnitude of heart (d) intermediate steps of morphological operation like opening (e) opening by reconstruction (f) opening-closing (g) opening –closing by reconstruction (h) Regional maxima super imposed on original image (i) modified regional maximasuperimposed by original image (j) markers and object boundaries (k) colored watershed label matrix (l) final super imposed color watershed result of heart image.*

We implemented these algorithms on a 64 bit operating system Window 7(Ultimate), Mat Lab 7.13.0564 (R2011b) [10] (Intel Core i5 3.6 GHz and 4GB RAM). This paper implements and presents the edge detection methods like (a) Sobel Operator (b) Prewitt Operator (c) Roberts operator (d) Log operator (e) Zero Crossing (f) Canny Method. Edge detection method gives edge information of image. Then proposed marker based watershed algorithm is implemented. Proposed segmentation techniques results show gradient magnitude of the original image of heart, proposed watershed transform of gradient magnitude of heart,intermediate steps of morphological operation like opening, opening by reconstruction, opening-closing, opening –closing by reconstruction, Regional maxima super imposed on original image, modified regional maxima superimposed by original image, watershed ridge lines, markers and object boundaries, colored watershed label matrix and final super imposed color watershed result of heart image.

Table 1 represents the assessment parameter formulas. Table 2 and Table 3 represent the quantitative values of edge detection techniques and proposed marker based watershed segmentation algorithm. The assessment parameters like Mean Square Error (MSE),Peak Signal to Noise Ratio (PSNR),Normalized Cross Co-relation (NCC), Average Difference (AD), Structural Content (SC),Maximum Difference(MD), Normalized Absolute Error(NAE), Mean(MEAN), Standard Deviation(STD), Co-Variance(COV), Universal Image Quality Index(UIQI), Cross –Correlation (CC),Structural Similarity Index(SSI) [11], Structural De Similarity Index(DSI) are used for evaluation of edge detection methods and proposed marker based watershed algorithm. Graphs show representation of all methods and their respective values.

TABLE 1: ASSESSMENT PARAMETER FORMULAS FOR EDGE DETECTION and IMAGE SEGMENTION

Name of Parameters	Formulas	Actual Trends match with Ideal Trends
Mean Square	$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(x_{m,n} - \bar{x}_{m,n})^2$	decreasing
Peak Signal to Noise Ratio	$PSNR = 10\log\frac{(2^n - 1)^2}{MSE} = 10\log\frac{255^2}{MSE}$	increasing
Normalizes Cross-Correlation	$NCC = \sum_{m=1}^{M}\sum_{n=1}^{N}(x_{m,n} \cdot \bar{x}_{m,n}) \Big/ \sum_{m=1}^{M}\sum_{n=1}^{N} x^2_{m,n}$	increasing

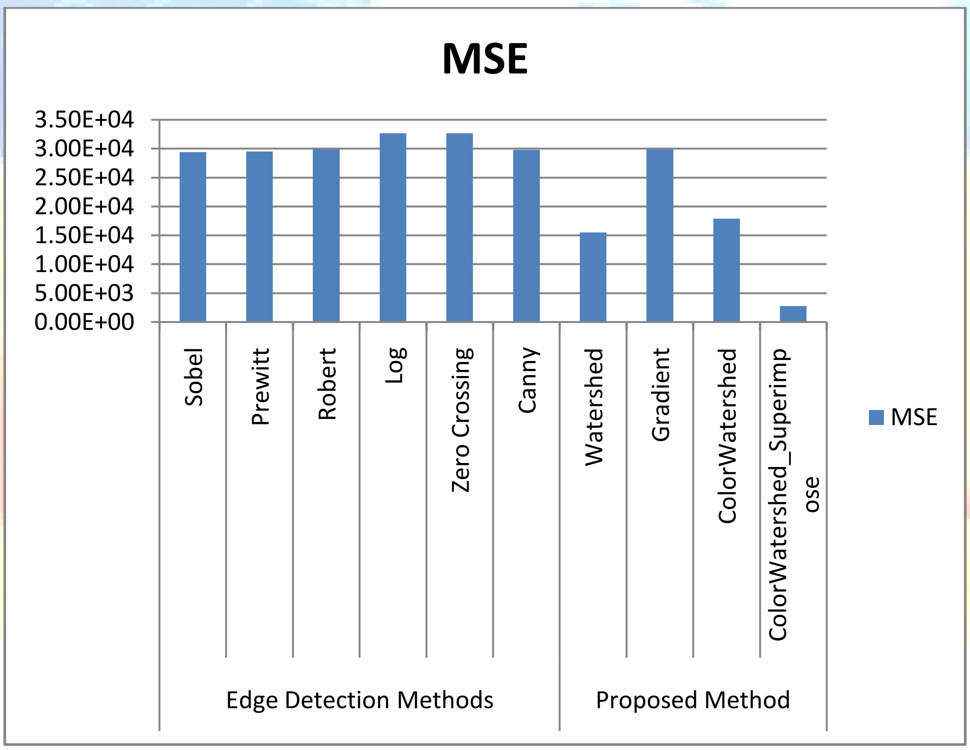
Average Difference	$AD = \sum_{m=1}^{M}\sum_{n=1}^{N}(x_{m,n} - \bar{x}_{m,n}) \Big/ MN$	decreasing
Structural Content	$SC = \sum_{m=1}^{M}\sum_{n=1}^{N} x_{m,n}^2 \Big/ \sum_{m=1}^{M}\sum_{n=1}^{N} \bar{x}_{m,n}^2$	decreasing
Normalized Absolute Error	$NAE = \sum_{m=1}^{M}\sum_{n=1}^{N} \lvert x_{m,n} - \bar{x}_{m,n} \rvert \Big/ \sum_{m=1}^{M}\sum_{n=1}^{N} \lvert x_{m,n} \rvert$	decreasing

TABLE 2:ASSESSMENT PARAMETER VALUES FOR EDGE DETECTION and IMAGE SEGMENTION

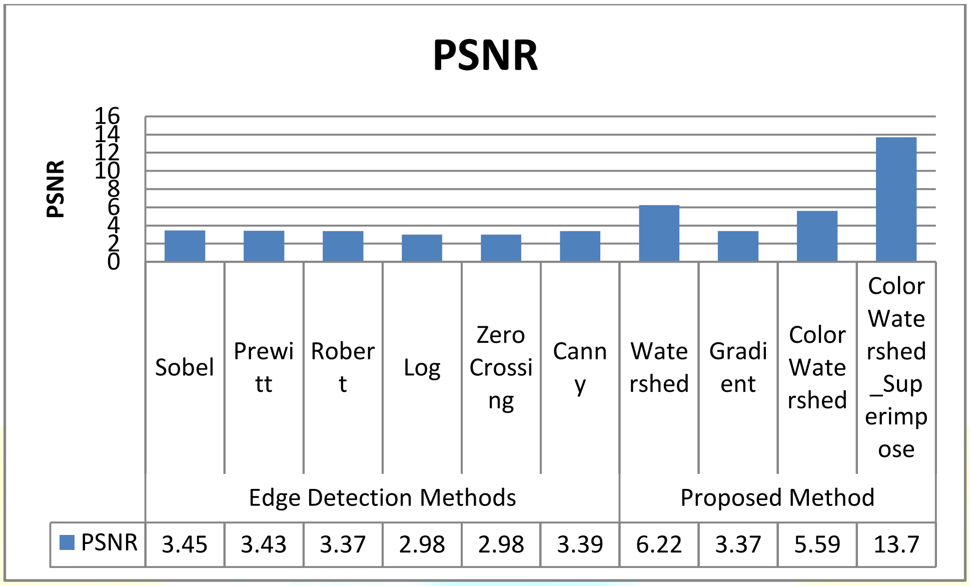
	Methods	MSE	PSNR	NCC	AD	SC	MD	NAE	MEAN
Edge Detection Methods	Sobel	2.94E+04	3.4516	0.0966	141.8995	16.437	255	0.894	25.2595
	Prewitt	2.95E+04	3.4337	0.0969	140.7813	15.3561	255	0.9056	26.3777
	Robert	2.99E+04	3.3787	0.0921	142.0128	15.0272	255	0.9051	25.1461
	Log	3.27E+04	2.9824	0.0214	162.3746	106.4733	255	0.9847	4.7843
	Zero Crossing	3.27E+04	2.9861	0.0217	162.3585	109.1005	255	0.9843	4.8005
	Canny	2.98E+04	3.3911	0.0838	145.3629	21.1078	255	0.903	21.7961
Proposed Method	Watershed	1.55E+04	6.2248	0.6598	22.0248	1.2856	216	0.6432	145.1341
	Gradient	2.99E+04	3.377	0.1314	136.6976	6.872	255	0.9174	30.4614
	ColorWatershed	1.79E+04	5.5939	0.5696	36.4941	1.4947	226	0.6115	130.6649
	ColorWatershed _Superimpose	2.77E+03	13.7026	0.8439	11.6451	1.2993	245	0.229	155.5138

TABLE 3:ASSESSMENT PARAMETER VALUES FOR EDGE DETECTION and IMAGE SEGMENTION

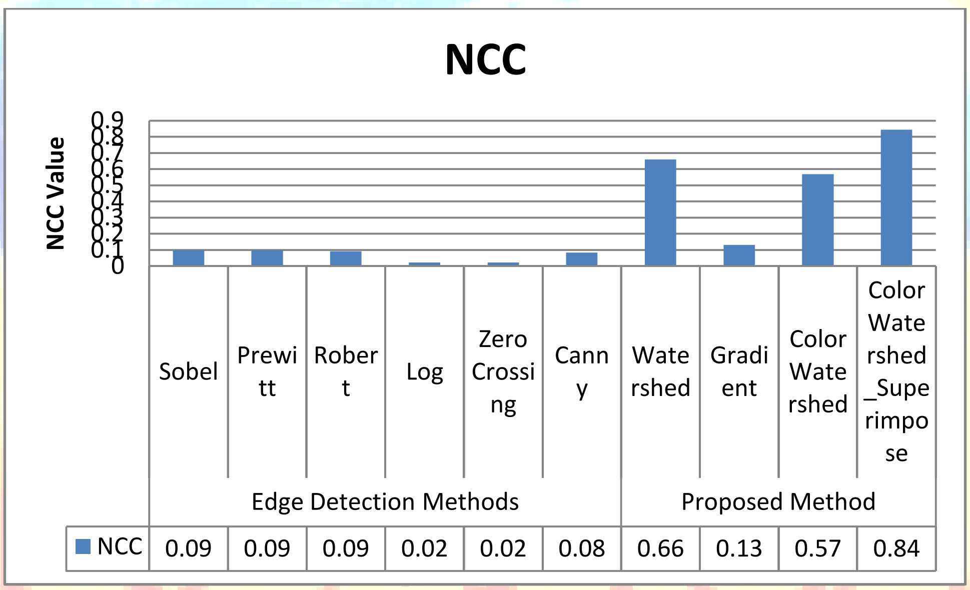
	Methods	STD	COV	UIQI	CC	SSI	DSI
Edge Detection Methods	Sobel	37.7015	-952.822	-0.0768	-0.3288	-0.0739	0.9312
	Prewitt	38.841	-1.13E+03	-0.0937	-0.3778	-0.0906	0.917
	Robert	40.2532	-1.09E+03	-0.0849	-0.3509	-0.082	0.9242
	Log	17.1767	-76.4609	-0.0014	-0.0579	-8.65E-04	0.9991
	Zero Crossing	16.9479	-68.8565	-0.0013	-0.0529	-7.29E-04	0.9993
	Canny	33.5955	-807.593	-0.0589	-0.3127	-0.0563	0.9467
Proposed Method	Watershed	72.5766	-1.92E+03	-0.3409	-0.3449	-0.334	0.7496
	Gradient	63.23	-643.324	-0.0458	-0.1324	-0.0435	0.9583
	ColorWatershed	74.6584	-2.56E+03	-0.4327	-0.4461	-0.4256	0.7015
	ColorWatershed_Superimpose	43.2277	2.57E+03	0.6593	0.7736	0.6618	2.9569



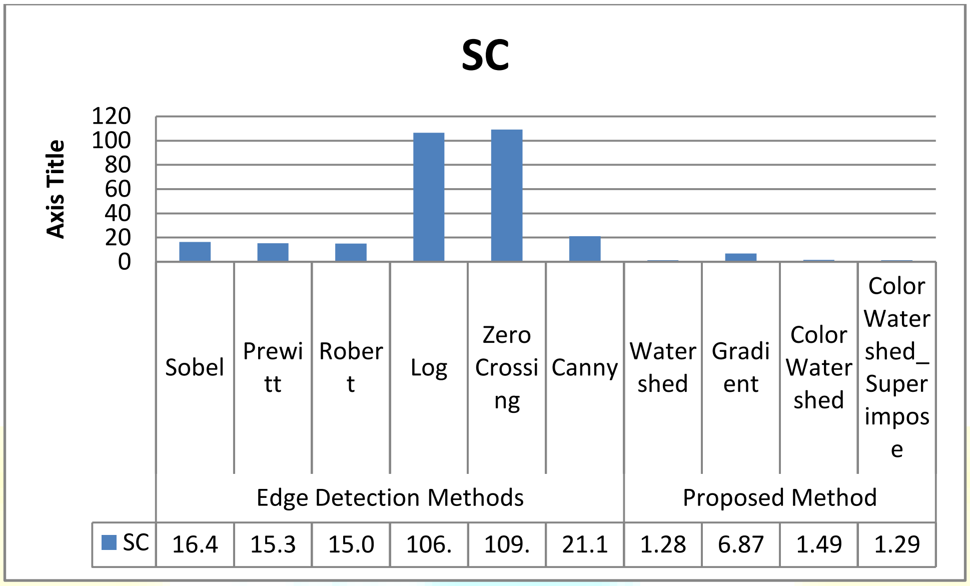
(a)


PSNR
PSNR
16
14
12
10
8
6
4
2
0
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
PSNR 3.45 3.43 3.37 2.98 2.98 3.39 6.22 3.37 5.59 13.7

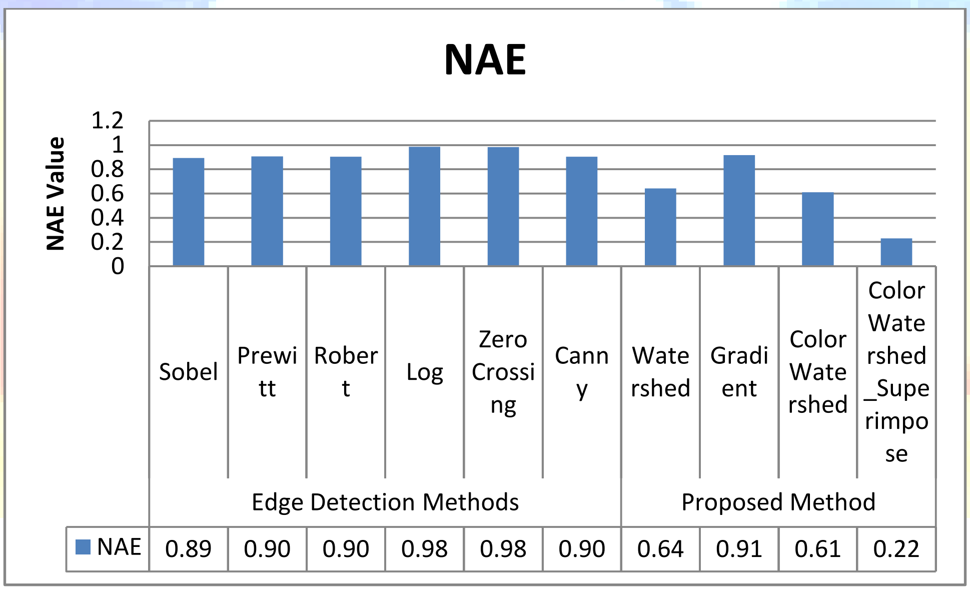
(b)


NCC
NCC Value
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
NCC 0.09 0.09 0.09 0.02 0.02 0.08 0.66 0.13 0.57 0.84

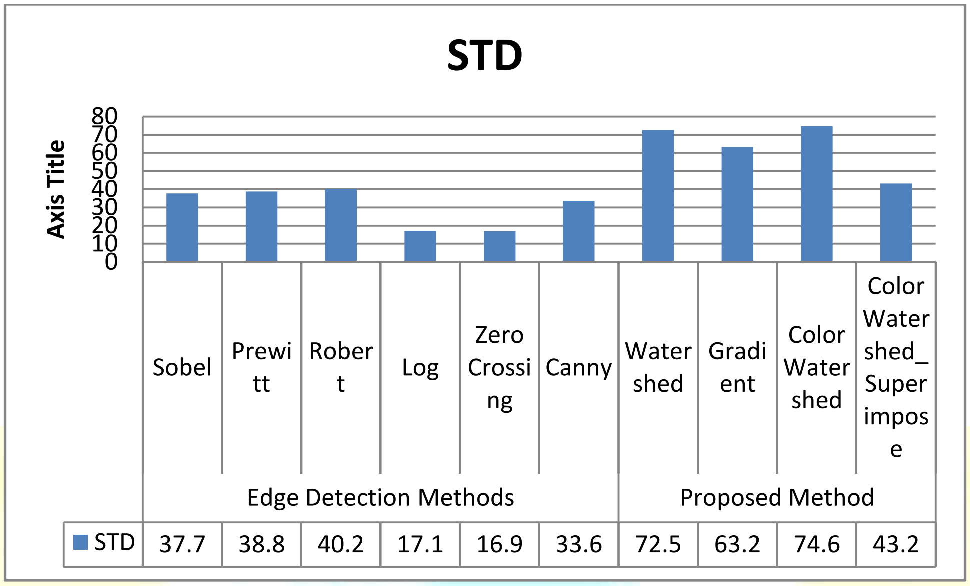
(c)


SC
Axis Title
120
100
80
60
40
20
0
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
SC
16.4
15.3
15.0
106.
109.
21.1
1.28
6.87
1.49
1.29

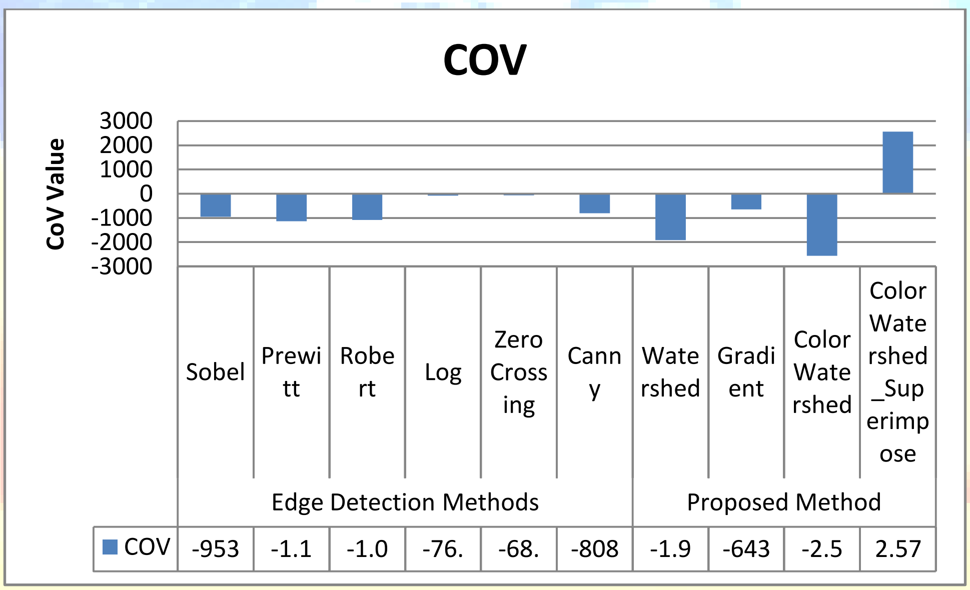
(d)


NAE
NAE Value
1.2
1
0.8
0.6
0.4
0.2
0
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
NAE
0.89
0.90
0.90
0.98
0.98
0.90
0.64
0.91
0.61
0.22

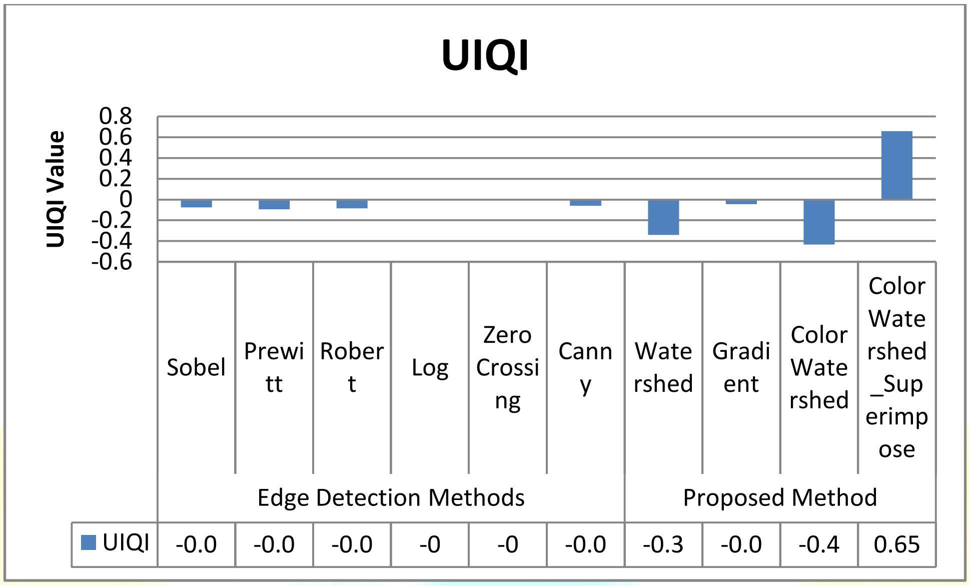
(e)


STD
Axis Title
80
70
60
50
40
30
20
10
0
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
STD
37.7
38.8
40.2
17.1
16.9
33.6
72.5
63.2
74.6
43.2

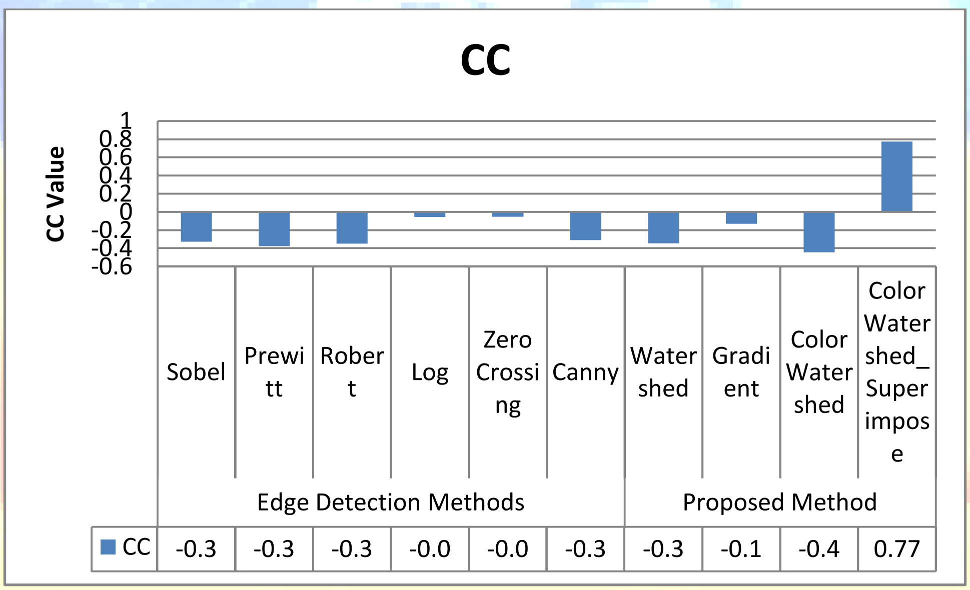
(f)


COV
CoV Value
3000
2000
1000
0
-1000
-2000
-3000
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
COV
-953
-1.1
-1.0
-76.
-68.
-808
-1.9
-643
-2.5
2.57

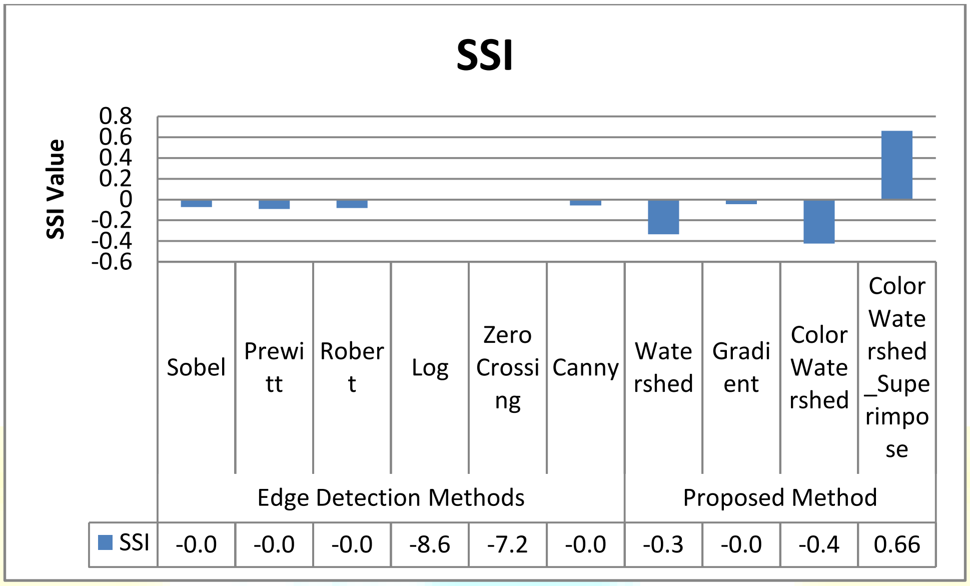
(g)


UIQI
UIQI Value
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
UIQI
-0.0
-0.0
-0.0
-0
-0
-0.0
-0.3
-0.0
-0.4
0.65

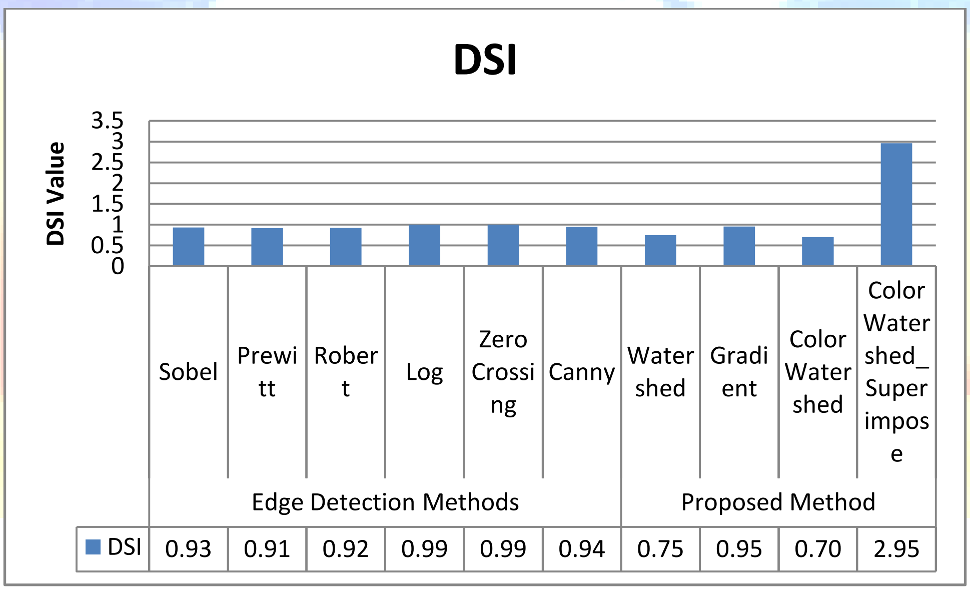
(h)


CC
CC Value
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Sobel
Prewitt
Robert
Log
Zero Crossing
Canny
Watershed
Gradient
Color Watershed
Color Watershed_Superimpose
Edge Detection Methods
Proposed Method
CC
-0.3
-0.3
-0.3
-0.0
-0.0
-0.3
-0.3
-0.1
-0.4
0.77

(i)



(j)



(k)

Figure 7 Graphs of (a) MSE (b) PSNR (c) NCC (d) SC (e) NAE (f) STD (g) COV (h) UIQI (i) CC (j) SSI (k) DSI

As seen from graph of MSE, the value of MSE is lower for proposed marker based watershed segmentation technique, which is desirable. Similarly as seen from graph of PSNR, the value of PSNR is higher for proposed marker based watershed segmentation technique, which is desirable. Similarly, higher value of NCC for proposed technique, which is desirable. Structural content values are lower for proposed technique, which is desirable. NAE values are lower for proposed technique, which is desirable. STD is less for zero crossing method of edge detection. UIQI value for result of color watershed superimposed is 0.659, which is towards 1, is higher for proposed marker based watershed segmentation technique, which is desirable.Similarly the value of CC for result of color watershed superimposed is 0.774, which is towards 1, is higher for proposed marker based watershed segmentation technique, which is desirable. Similarly the value of SSI for result of color watershed superimposed is 0.662, which is towards 1, is higher for proposed marker based watershed segmentation technique, which is desirable. The DSI value of result of watershed transform is 0.75, result of color watershed is 0.702, which are desirable. For result of color watershed superimposed is 2.957, is higher for proposed marker based watershed segmentation technique, which is desirable.

6. Applications

Some of the practical applications of image segmentation are:

- Medical Imaging and Analysis
  - Locate tumors and other pathologies
  - Measure tissue volumes
  - Computer-guided surgery
  - Diagnosis
  - Treatment planning
  - Study of anatomical structure

7. Conclusion

This paper presents edge detection methods and segmentation technique.This paper implements and presents the edge detection methods like (a) Sobel Operator (b) Prewitt Operator (c) Roberts operator (d) Log operator (e) Zero Crossing (f) Canny Method. Edge detection method gives edge information of image. Then proposed marker based watershed algorithm is implemented. This research paper shows that proposed marker based watershed segmentation technique is superior as compared to edge detection methods. Heart image is taken as an input image, so in general our algorithm is also applicable to various modalities of medical images. Here standard assessment parameters are used for assessing the resultant values and all methods results are plotted in Graphs.

References

[1] Rafael C., Gonzalez, and Richard E. Woods, Digital Image Processing 3rd ed., New Delhi ,Published by Pearson Education First Impression, 2009

[2] Rafael C., Gonzalez, and Richard E. Woods, Steven L. Eddins, Digital Image Processing Using MATLAB, 2nd Indian reprint, Delhi, Published by Pearson Education, 2005

[3] Milan Sonka, Vaclav Hlavac, Roger Boyle, Image Processing, Analysis and Machine Vision, 2nd ed., Bangalore , by Thomson Asia Pte Ltd., Singapore, first reprint 2001

[4] Anil k. Jain, Fundamentals of Digital Image Processing, Delhi, Published by Pearson Education, , 3rd Impression, 2008

[5] W.K. Pratt, Digital Image Processing. , John Wiley and Sons, New York.

[6] S.Lanser. Kantenorientic Frbsegmentation CTE-Lab Raum,Proc. 15th DAGM Symposium Mustererkennung, 1993,pp. 639-646

[7] Meyer F. and Beucher S., “Morphological Segmentation”, Journal of Visual Communication and Image representation, Vol. 1, no. 1, pp. 21-46, Sept.1990, Academic Press.

[8] Arnau Oliver, Jordi Freixenet, Joan Marti, Elsa Perez, Josep Pont, Erika R.E. Denton, Reyer Zwiggelaar, A review of automatic mass detection and segmentation in mammographic images, Medical Image Analysis 14 (2010) 87–110.

[9] L. Vincent, P. Soille, Watersheds in digital spaces: an efficient algorithm based on immersion simulations, IEEE Trans. on PAMI, vol. 13, no. 6, pp. 583–598, 1991.

[10] http://www.mathworks.com

[11] www.wikipedia.org