

# Medical Image Segmentation based on Vigorous Smoothing and Edge Detection Ideology

Jagadish H. Pujar, Pallavi S. Gurjal, Shambhavi D. S, Kiran S. Kunnur

**Abstract**—Medical image segmentation based on image smoothing followed by edge detection assumes a great degree of importance in the field of Image Processing. In this regard, this paper proposes a novel algorithm for medical image segmentation based on vigorous smoothing by identifying the type of noise and edge detection ideology which seems to be a boom in medical image diagnosis. The main objective of this algorithm is to consider a particular medical image as input and make the preprocessing to remove the noise content by employing suitable filter after identifying the type of noise and finally carrying out edge detection for image segmentation. The algorithm consists of three parts. First, identifying the type of noise present in the medical image as additive, multiplicative or impulsive by analysis of local histograms and denoising it by employing Median, Gaussian or Frost filter. Second, edge detection of the filtered medical image is carried out using Canny edge detection technique. And third part is about the segmentation of edge detected medical image by the method of Normalized Cut Eigen Vectors. The method is validated through experiments on real images. The proposed algorithm has been simulated on MATLAB platform. The results obtained by the simulation shows that the proposed algorithm is very effective which can deal with low quality or marginal vague images which has high spatial redundancy, low contrast and biggish noise, and has a potential of certain practical use of medical image diagnosis.

**Keywords**—Image Segmentation, Image smoothing, Edge Detection, Impulsive noise, Gaussian noise, Median filter, Canny edge, Eigen values, Eigen vector.

## I. INTRODUCTION

IMAGE segmentation has been a powerful tool in analyzing the content of an image so as to know the information it stores. At present, image data visualization, especially visualization of medical image (such as X-ray, Computer Tomography (CT), Magnetic Resonance Image (MRI) and Position Emission Tomography (PET)), has become one of the hotspots of image processing research after 20 years development. Image segmentation and contour extraction are the most intuitive methods for medical image visualization. By extracting the edge of the interested template, organize and pathological area, we can get the purpose of adjuvant therapy, surgical planning, teaching model, prosthetic design and etc.

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However, medical images are usually characterized by faded features utilizing a narrow distribution of gray-levels. Because of this reason, medical image often suffers from high spatial redundancy and low contrast that can be further degraded by the noise introduced in the process of imaging. Therefore, extraction of useful information accurately and rapidly from medical image becomes a certain degree of difficulty. Moreover, automatic extraction of continuous contour points is complicated by discontinuity of edges in the back of the organs.

Partitioning of an image into several constituent components is called Image segmentation. Segmentation is an important part of practically any automated image recognition system, because it is at this moment that one extracts the interesting objects, for further processing such as description or recognition. Segmentation of an image is in practice the classification of each image pixel to one of the image parts. Image segmentation has been the subject of considerable research activity over the last three decades. But segmenting the colour images has received much less attention of scientific community. In computer vision literature, various methods dealing with segmentation and feature extraction are discussed, which can be broadly grouped into region based techniques, edge based techniques, hybrid methods which combine edge and region methods, and so on.

Image segmentation is an essential preliminary step in most automatic pictorial pattern recognition and scene analysis problems. It is one of the most difficult tasks in image processing. Image segmentation is the process of partitioning a digital image into multiple regions or clusters. Each region is made up of sets of pixels. Image segmentation simplifies and changes the representation of an image. i.e. the image is transferred into something that is more meaningful and easier to analyze [1].

This work proposes an algorithm to accounts for the above task and produces a processed output which is quick ready for analysis. The current methods of contour extraction can be roughly divided into three categories presently: First, the image is converted to gray scale and tracking contour of the borders to extract curves. For affecting by non-uniform coverage and noise, etc., it is difficult to find the appropriate threshold of the medical image, so the accuracy of contours will be affected; Second, using classic edge detection to extract the edge of images, such as Robert operator, Sobel operator, Laplace operator, etc. This method cannot extract

continuous contour line; Lastly, the overall extraction based on the minimum standards of energy, such as relaxation method, the neural network analysis method. This method limits the range of the capture, often requires an initial contour, and cannot detect the concave part of the object. In this paper, an improved method is provided for extracting the continuous boundary contours of some images presented, in particular the edge boundary of the image, which includes pre-processing algorithms, filtering algorithms and contour extraction algorithms.

## II. MEDICAL IMAGE NOISE IDENTIFICATION USING LOCAL HISTOGRAMS

This method primarily consists of roughly segmenting and labeling the noisy image. The image of labels is then used for the selection of homogeneous regions. This is a new way of identifying homogeneous regions. This is accomplished by roughly segmenting the noisy image using a multi-thresholding technique. The Peak detection and valley extraction algorithm (*PDVE*) which analyses the histogram step by step and finally extracts the valleys required as threshold value for segmentation. The basis of histogram analysis approach is that the regions of interest tend to form modes (a dominating peak that can represent a region) in the corresponding histogram. Then, a typical histogram analysis generally carried out by using the following three steps:

**Step1:** Recognize the dominant modes of the histogram.

**Step2:** Find the valleys between different modes.

**Step3:** Apply the extracted thresholds to the image for segmentation.

As we know, the noise is unwanted information. The variation is generally referred to as noise. Noise is an important defect in the image that can take many different forms and arises from various sources such as heat generated might free electrons from the image sensors itself, thus contaminating the "true" photoelectrons. Noise is a disturbance that affects a signal and may distort the information carried by the signal. Image noise can also be originated due to the electronic noise in the sensors in the digital cameras or scanner circuitry. Many types of noises exist today, but this method the medical image noise is identified and broadly classified as additive, multiplicative or impulsive.

In order to identify the type of noise affecting the medical image, the behavior of the dynamics of the grey levels of the local homogeneous regions are analyzed. Each of the local homogeneous regions must have at least 128 pixels. This value varies from image to image based on its size.

The identification of type of noise in the medical image is carried out in two stages. In the first stage, a criterion is used to detect the presence of the impulsive noise. If the result of this criterion is negative, the image is then submitted to second stage of another criterion in order to identify either the additive or multiplicative nature of the noise.

### A. Detection of Impulsive Noise

If the ratio of the mean of the dynamics of the grey levels of the homogeneous regions to the maximum value of the dynamics of the grey levels of the homogeneous regions is greater than a threshold value than the noise affecting the image is declared to be an impulsive noise.

### B. Detection of Additive or Multiplicative Noise

Histograms of the different labels given to the image are constructed and the dynamics of these histograms are computed. If the evolution of the dynamic fluctuates around a constant value, then it is declared as additive noise. If the dynamic fluctuates around a line passing through zero then it is declared as multiplicative noise. The decision criteria used here is based on a mathematical formulation which is given below:

$$\left(\frac{A}{B}\right) > \left(\frac{C}{D}\right) \quad (1)$$

The above equation denotes that the fraction A/B should be less than C/D if it has to be an additive noise else it is designated as multiplicative noise. In the above equation B corresponds to the average of the of the estimated local standard deviation and A corresponds to the dispersion factor of A. whereas D corresponds to the average of the relationship between the local standard deviation and the local average and C corresponds to the dispersion factor associated with D.

## III. MEDICAL IMAGE SMOOTHING

Medical image smoothing is the process of removing the noise from the observed noisy image to render the original image. Image denoising was first investigated in the 1970's at USC. Thereafter a lot of development in this field has been done and lots of algorithms have been proposed to restore the noisy image. During image acquisition or transmission, medical images are often contaminated by impulsive, additive or multiplicative noise due to a number of non-idealities in the imaging process. The noise usually corrupts images by replacing some of the pixels of the original image with new pixels having luminance values near or equal to the minimum or maximum of the allowable dynamic luminance range. In the most applications, it is very important to remove noise from image data, since the performances of subsequent image processing tasks are strictly dependent on the success of image noise removal operation. However, this is a difficult problem in any image processing system because the restoration filter must not distort the useful information in the image and preserve image details and texture while removing the noise [2].

The denoisation of the medical image is carried out in two stages. In the first stage, a criterion is used to denoise the presence of the impulsive noise using a suitable window median filter as it is very effective for impulsive noise reduction. If the type of noise in the medical image is either additive or multiplicative, the image is then submitted to second stage of another criterion in order to denoise either the

additive or multiplicative noise using a suitable mask Gaussian filter or Frost filter respectively [19][22].

#### A. Impulsive Noise Smoothing

The medical images could be contaminated by impulsive noise during image acquisition or transmission. The intensity of this impulsive noise has a tendency of being relatively high or low. Thus it could severely damage the image and cause some loss of information details. Various filtering techniques have been proposed in the past, and it is well-known that linear filtering techniques could produce serious image blurring. As a result of this, non-linear filters have been exploited due to their much improved filtering performance, in terms of impulsive noise attenuation and edge preservation. One such filtering technique is the Median filtering which is basically a non-linear filter used to achieve good result in image restoration. The Standard Median filter exploits the rank-order information of pixel intensities within a filtering window and replaces the centre pixel in the window by the median of all the pixels nearest neighbor pixels of the window. Median filtering employs a 2D mask which is applied to each corrupt pixels of the medical image.

The approach made to develop an algorithm to denoise the impulsive noise of medical image is based on the knowledge of working principle of classical median filter. Consider that the image is of size  $m \times m$  of eight bit gray scale pixel resolution. In a  $3 \times 3$  window at  $(i,j)$ , the central pixel value is  $x$  and its neighbors are  $x_k$  where  $k=1$  to 8. Then the conventional median filter output  $y_{median}$  for corrupted pixel  $x$  is

$$y_{median} = \begin{cases} \text{median} \{x_k\}; & \text{if } |\text{median} \{x_k\} - x| > \text{threshold} \\ x & ; \text{otherwise} \end{cases} \quad (2)$$

#### B. Additive Noise Smoothing

The additive noise smoothing of the medical image is carried out by using a Gaussian filter. The Gaussian linear filter is a simple rank selection filter that attempts to remove Gaussian noise by convolving the given image with the Gaussian mask. Since the image is stored in discrete pixels, the Gaussian mask will be a discrete approximation of the 2-D Gaussian function. The size and the standard deviation are two important criteria that need to be taken into consideration when creating the Gaussian mask.

#### C. Multiplicative Noise Smoothing

The multiplicative noise smoothing of the medical image is carried out by using a Frost filter. The Frost filter replaces the pixel of interest with a weighted sum of the values within the  $m \times m$  moving window. The weighting factors decrease with distance from the pixel of interest. The weighting factors increase for the central pixels as variance within the window increases [22].

### IV. IDEOLOGY OF MEDICAL IMAGE EDGE DETECTION

Edge detection is a process of identifying an edge. The sharp change in image pixel intensity is identified as the edge of the image. Edges correspond to points in the image where the gray value changes significantly from one pixel to the next pixel. Edge detection of an image significantly reduces the amount of data and filters out redundant information, while preserving the vital structural properties in an image. Sound edge detection will provide valuable information for further processing of an image such as image segmentation, image enhancement, image registration, identifying object in scene etc. Edge detection is done using various methods such as gradient method and Laplacian method, edge detection using gradient method is implemented in this work using Canny algorithm.

#### A. Canny Edge Detection Technique

The Canny edge detection algorithm is known to many as the optimal edge detector. Canny's intentions were to enhance the many edge detectors already out at the time he started his work. The first and most obvious is low error rate. It is important that edges occurring in images should not be missed and that there be NO responses to non-edges. The second criterion is that the edge points be well localized. In other words, the distance between the edge pixels as found by the detector and the actual edge is to be at a minimum. A third criterion is to have only one response to a single edge.

Based on these criteria, the Canny edge detector first smoothes the image to eliminate and noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (non maximum suppression). The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero (made a non edge). If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above  $T_2$  [7].

In order to implement the canny edge detector algorithm, a series of steps must be followed. The first step is to filter out any noise in the original image before trying to locate and detect any edges. And because the Gaussian filter can be computed using a simple mask, it is used exclusively in the Canny algorithm. Once a suitable mask has been calculated, the Gaussian smoothing can be performed using standard convolution methods. The larger the width of the Gaussian mask, the lower is the detector's sensitivity to noise. The localization error in the detected edges also increases slightly as the Gaussian width is increased.

After smoothing the image and eliminating the noise, the next step is to find the edge strength by using Sobel operator, in accordance with below description. Sobel edge operator

method uses first order derivative, gradient method to find the edge. First order derivative based techniques depend on computing the gradient several directions and combining the result of each gradient. The value of the gradient magnitude and orientation is estimated using Horizontal and Vertical convolution masks [20].

The gradient is a vector, whose components measure how rapid pixel value are changing with distance in the  $x$  and  $y$  direction. Thus, the components of the gradient may be found using the following approximation.

$$\frac{\partial f(x, y)}{\partial x} = \Delta x = \frac{f(x+dx, y) - f(x, y)}{dx} \quad (3)$$

$$\frac{\partial f(x, y)}{\partial y} = \Delta y = \frac{f(x, y+dy) - f(x, y)}{dy} \quad (4)$$

In order to detect the presence of a gradient discontinuity, one could calculate the change in the gradient at  $(i, j)$ . This can be done by finding the following magnitude measure.

$$G = \sqrt{Gx^2 + Gy^2} \quad (5)$$

And the gradient direction is given by

$$\theta = \tan^{-1} \left[ \frac{Gy}{Gx} \right] \quad (6)$$

The next step after the edge detection is edges are subjected to non-maximum suppression using edge direction. Finding the edge direction is trivial once the gradient in the  $x$  and  $y$  directions are known. However, you will generate an error whenever  $\text{sum}X$  is equal to zero. So in the code there has to be a restriction set whenever this takes place. Whenever the gradient in the  $x$  direction is equal to zero, the edge direction has to be equal to 90 degrees or 0 degrees, depending on what the value of the gradient in the  $y$ -direction is equal to. If  $Gy$  has a value of zero, the edge direction will equal 0 degrees. Otherwise the edge direction will equal 90 degrees computed.

Then, it can be seen that, there are only four possible directions when describing the surrounding pixels - 0 degrees (in the horizontal direction), 45 degrees (along the positive diagonal), 90 degrees (in the vertical direction), or 135 degrees (along the negative diagonal). So now the edge orientation has to be resolved into one of these four directions depending on which direction it is closest to (e.g. if the orientation angle is found to be 3 degrees, make it zero degrees).

Therefore, any edge direction falling within 0 to 22.5 & 157.5 to 180 degrees is set to 0 degrees. Any edge direction falling within 22.5 to 67.5 degrees is set to 45 degrees. Any edge direction falling within 67.5 to 112.5 degrees is set to 90 degrees. And finally, any edge direction falling within 112.5 to 157.5 degrees is set to 135 degrees.

After the edge directions are known, non-maximum suppression now has to be applied. Non-maximum suppression is used to trace along the edge in the edge

direction and suppress any pixel value (sets it equal to 0) that is not considered to be an edge. This will give a thin line in the output image.

## V. IDEOLOGY OF MEDICAL IMAGE SEGMENTATION

Image segmentation is typically used to locate objects of interest and boundaries like lines, curves in an image. The pixels of a colour image are represented as vectors. In graph partition, the image is converted into an undirected weighted graph [8] [10]. Every pixel in the image corresponds to a vertex of a graph. And the weight on one edge is assigned according to the similarity between two corresponding pixels. The criteria of similarity are different in different applications. In general, the similarity can be defined by the distance, color, gray level, textures and so on [5]. Considering the computation of the algorithm, we usually restrict the relationship of pixels in a neighborhood. Given a connected graph  $G = (V, E)$  with a vertex set  $V$  and edge set  $E$ , the goal is to find an edge cut which separates the graph into  $k$  disjoint subsets such that  $V = \bigcup_{i=1}^k v_i$  and  $\forall(i, j)$  and  $v_i \cap v_j = \emptyset$ .

We define that an edge cut  $C$  is a set of edges whose removal makes the graph disconnected.

$$\text{cut}(C) = \sum_{e \in C} w(e) \quad (7)$$

A graph  $G = (V, E)$  can be partitioned into two disjoint sets,  $A, B$ . Where,  $\text{cut}(A, B) = \sum_{p \in A, q \in B} W_{pq}$

The measure of normalized cut can be written as:

$$N_{\text{cut}}(A, B) = \sum_{p \in A, q \in B} W_{pq} \left( \frac{1}{\sum_{p \in A} D_p} + \frac{1}{\sum_{q \in B} D_q} \right) \quad (8)$$

Where,  $D_p = \sum_{q \in V} W_{pq}$ , is defined as degree of vertex  $p$ . The normalized cut measures both the total dissimilarity between the different groups like Eq. 10, as well as the total similarity within groups.

To minimize the normalized cut, they deduced an efficient computational technique based on a generalized eigen value problem. First, we define  $W$  as the affinity matrix of the graph, and  $W(i, j) = w(i, j)$ ;  $D$  is a diagonal matrix, in which each element along the diagonal represents the degree of correspondent vertex  $i$ ,  $D_i$ ;  $x$  is a label vector, if vertex  $i$  is in sub-graph  $A$ ,  $x(i) = 1$ ; otherwise  $x(i) = -1$ . Based on these notations, minimizing normalized cut results in the following objective function:

$$\min N_{\text{cut}}(A, B) = \min \frac{y^T (D - W) y}{y^T D y} \quad (9)$$

With the conditions  $y_i \in \{1, -1\}$  and  $y^T D y = 0$ , where  $b$  is constant less than 1. The eigenvector of  $D - b(D - W)$  corresponding to the smallest non-zero eigen value is an approximation. Then corresponding eigenvector is split into two parts by a threshold.

## VI. PROPOSED MEDICAL IMAGE SEGMENTATION ALGORITHM IMPLEMENTATION

In this paper we propose a novel approach to segment image using graph partitioning and formation of normalized cuts using eigen values. In graph partition, the image is converted into an undirected weighted graph. Every pixel in the image corresponds to a vertex of a graph. And the weight on one edge is assigned according to the similarity between two corresponding pixels. The criteria of similarity are different in different applications. In general, the similarity can be defined by the distance, colour, gray level, textures and so on. Considering the computation of the algorithm, we usually restrict the relationship of pixels in a neighborhood [4].

**Step1:** Identify the type of noise present in the given medical image using local histograms.

- Find the set of points corresponding to the local maximums of the histogram.

$$P_0 = \{i, h(i) \mid h(i) > h(i-1) \& h(i) > h(i+1)\} \quad (10)$$

- Consider local neighborhood of consecutive three bins of histogram and find maximum frequency value.

$$P_1 = \{P_i, h(P_i) \mid h(P_i) > h(P_i-1) \& h(P_i) > h(P_i+1) \mid P_i \in P_0\} \quad (11)$$

- If a peak is too small compared to the biggest peak, then it is removed. Find  $y_{\max}$ ; If  $y_i/y_{\max} < 0.02$  then remove  $y_i$

- Choose one peak if two peaks are too close.

$$h(P_1) \& h(P_2), P_2 > P_1, P_2 - P_1 < 10 \quad (12)$$

$$h = \max\{h(P_1), h(P_2)\} \quad (13)$$

- Ignore a peak if the valley between two peaks is not palpable.

$$\text{Havg} = \text{sum}(\text{counts}(P_1:P_2)) / (P_2 - P_1 + 1) \quad (14)$$

- Extract valleys as thresholds and perform labeling of image for selection of homogeneous regions. Hence, apply the block of size  $m \times m$  for each pixel of the observed image and analyze the dynamics  $D(n)$  of the grey levels of the  $M$  local homogenous regions of the observed image.

- Compute mean and maximum of dynamics  $D(n)$ ,  $(A/C)$  and  $(B/D)$ .

- If  $(\text{mean}(D(n)) / \max(D(n))) > \lambda$  then the noise present in the medical image is impulsive one. Elseif  $(A/C) > (B/D)$  then the noise present in the medical image is multiplicative one. Else the noise present in the medical image is additive one.

**Step2:** Carryout the medical image smoothing by selecting respective image noise reduction filters.

- If the noise present in the medical image is impulsive one then apply Median filter to reduce this noise.
- Else if the noise present in the medical image is multiplicative one then apply Frost filter to reduce this noise.
- Else apply Gaussian filter to reduce the additive noise of the medical image.

**Step3:** Detect the edge of the smoothened medical image using canny edge detection technique.

- Calculate  $\bar{G}_x$  and  $\bar{G}_y$ .

- Calculate absolute magnitude gradient  $G$ , store it in the resultant matrix.

- Calculate two threshold values  $T1$  and  $T2$  and apply it to gradient matrix, i.e. if the gradient is greater than upper threshold value then it considered as edge. Then consider the lower threshold value, if the gradient value lies in between  $T1$  and  $T2$ , then it is considered as edge if one of its neighbor is an edge.

- Calculate directional matrix and perform non maximum suppression.

**Step4:** Carryout the medical image segmentation

- Resize the smoothened and edge detected medical image to a size of  $160 \times 160$ .

- Input arguments are the compressed image [21] and number of segments required for the segmentation which are initialized.

- Obtain the similarity matrix  $W$  based on Intervening Contours (edges). The graph edge weight connecting two nodes  $i$  and  $j$  can be defined as follows;

$$W_{i,j} = e^{\frac{-\|F(i)-F(j)\|_2^2}{\sigma_f^2} + \frac{-\|X(i)-X(j)\|_2^2}{\sigma_x^2}} \quad (15)$$

Where  $X(i)$  is the spatial location of node  $i$ , i.e., the coordinates in the original image  $I$ , and  $F(i)$  is a feature vector defined as:

$F(i) = 1$  for segmenting point sets,

$F(i) = I(i)$ , the intensity value, for segmenting brightness (gray scale) images,

$F(i) = [v, u \cdot s \cdot \sin(h), v \cdot s \cdot \cos(h)](i)$ , where  $h, s, v$  are the HSV values, for color segmentation,

$F(i) = [|I_{f1}|, \dots, |I_{fn}|](i)$

- Solving a standard eigen value problem for all eigenvectors, one can take 0 or the median value as the splitting point or one can search for the splitting point such that the resulting partition has the best  $N_{cut}$  value.

- The eigen values are discretized for the number of segments required.

- Then the image with eigen the values is the segmented image.

## VII. PROPOSED ALGORITHM SIMULATION AND RESULT ANALYSIS

As we know that the image segmentation is the process of partitioning a digital image into multiple regions or clusters. Each region is made up of sets of pixels. Image segmentation simplifies and changes the representation of an image. i.e. the image is transferred into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects of interest and boundaries like lines, curves in an image. The pixels of a colour image are represented as vectors. The proposed algorithm developed based on this concept is validated by implementing a program on MATLAB platform and the simulated results are as shown in Fig.2 to Fig.8 for the noisy input medical image of Fig.1.

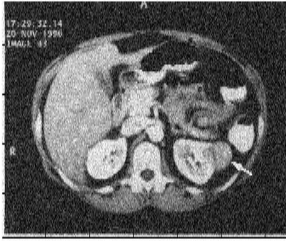


Fig. 1 Image with Gaussian noise.



Fig. 2 Smoothened Image

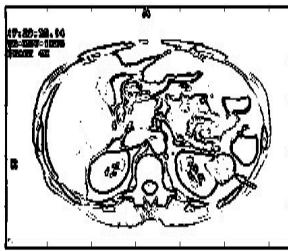


Fig. 3 Edge detected image



Fig. 4 Counter edge detected image

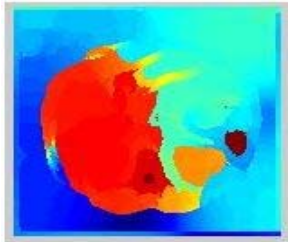
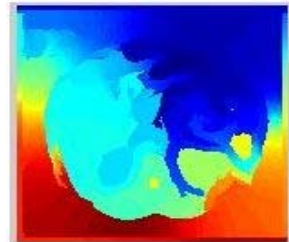
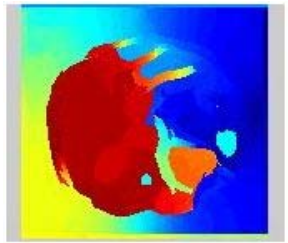
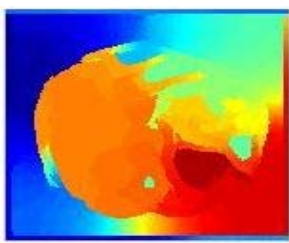
Fig. 5 First smallest eigen vector  
Segmented medical imageFig. 6 Second smallest eigen vector  
Segmented medical imageFig. 7 Third smallest eigen vector  
Segmented medical imageFig. 8 Fourth smallest eigen vector  
Segmented medical image

Fig.2 shows a gray scale of input image compressed to the size of 160x160 which is subjected to pre-processing task of rigorous smoothing by applying proposed filters after identifying the particular type of noise. Fig.3 shows the edges of pre-processed image are detected using canny edge detection technique. This image has varying intensities. Thus contour edges are detected as shown in Fig.4 which aid in the process of segmentation. Fig.5 to Fig.8 shows the first smallest eigen vector of generalised eigen value segmented medical image and the eigenvectors corresponding to the second smallest to the fourth smallest eigen values of segmented medical image. The eigenvectors are reshaped to the size of the image.

## VIII. ONCLUSIONS

Possibly the most important question surrounding the use of image segmentation is its application in clinical settings. Computerized segmentation methods have already demonstrated their utility in research applications and are now garnering increased use for computer aided diagnosis and radiotherapy planning. In this paper we were successful in developing algorithm to obtain fully fledged segmentation with rigorous smoothing and edge detection ideology. The chapter presents a algorithm which uses the shape constraint to improve the performance of the normalized cut for Image segmentation. Using the shape model, we can find the corresponding eigenvector to segment the target, even if the target is blurred or it is only a small part of the entire image which causes trouble to the conventional normalized cut method. With the modification of the affine matrix based on the shape constraint, we make the normalized cut more stable and robust. It is unlikely that automated segmentation methods will ever replace physicians but they will likely become crucial elements of medical image analysis. Segmentation methods will be particularly valuable in areas such as computer integrated surgery, where visualization of the anatomy is a critical component.

Future research in the segmentation of medical images will strive towards improving the accuracy, precision, and computational speed of segmentation methods, as well as reducing the amount of manual interaction. Accuracy and precision can be improved by incorporating prior information from atlases and by combining discrete and continuous-based segmentation methods. For increasing computational efficiency, multistage processing and parallelizable methods such as neural networks appear to be promising approaches. Computational efficiency will be particularly important in real-time processing applications.

## REFERENCES

- [1] Chen Tie Qi and Lu Yi, "Color image segmentation- an innovative approach. Pattern recognition", vol. 35, 2002, pp. 395-405. 134
- [2] Reginald L. Lagendijk and Jan Biemond, "Basic methods for Image Restoration and Identification", 15 February, 1999.
- [3] X.Z.Sun and Anastasios N. Venetsanopoulos, "Adaptive Schemes for Noise Filtering and Edge Detection by Use of Local Statistics", IEEE transactions on circuits and systems, vol 35, no. 1, January 1988.
- [4] Bellon Olga Regina Pereira, Dhirene Alexandre Ibrahim et al. Edge detection to guide image segmentation by clustering techniques, *International conference on image processing*, Vol. 2, pp. 725-729, 1999.
- [5] Cheriet M., Said J.N. and Suen C.Y., "A recursive thresholding technique for image segmentation", IEEE transactions on image processing, vol. 7, no.6, June 1998, pp. 918-921
- [6] Jianbo Shi and Jitendra Malik, "Normalized Cuts and Image Segmentation", IEEE transactions on pattern analysis and machine intelligence, vol. 22, no. 8, August 2000.
- [7] Neeta Nain, Gaurav Jindal, Ashish Garg and Anshul Jain, "Dynamic Thresholding Based Edge Detection", Proceedings of the World Congress on Engineering 2008 Vol I, 2008.
- [8] M. Kass and A.Witkin *et al.*, "Snakes - active contour models," *IJCV*, vol. 1, no. 4, pp. 321-331, 1987.
- [9] S. Osher and J. Sethian, "Fronts propagation with curvature dependent speed: Algorithms based on hamilton-jacobi formulations," *J. of Comp. Phy.*, vol. 79, pp. 12-49, 1988.

- [10] F.R. Hansen and H. Elliott, "Image segmentation using simple markov field models," *CGIP*, vol. 20, no. 2, pp. 101-132, October 1982.
- [11] G.A.Baxes, "Digital Image Processing Principles & Applications", Wiley & Sons, 1994.
- [12] Behrooz Ghandeharian, Hadi Sadoghi Yazdi, "Modified Adaptive Center Weighted Median Filter for suppressing Impulse noise in images", *International Journal of Research and Reviews in Applied Sciences*, 2009.
- [13] Kevin Liu, "An Implementation of the Median Filter and Its Effectiveness on Different Kinds of Images", *Computer Systems Lab*, 2006-2007.
- [14] Manfred Kopp and Werner Purgathofer, "Efficient 3x3 Median Filter Computations", *Institute of Computer Graphics*.
- [15] Rajoo Pandey, "An Improved Switching Median filter for
- [16] *Uniformly Distributed Impulse Noise Removal*", *World Academy of Science, Engineering and Technology* 38 2008.
- [17] Gerasimos Louverdis, Ioannis Andreadis and Antonios Gasteratos, "A new content based Median Filter", *Department of Electrical & Computer Engineering, Democritus University of Thrace*.
- [18] W. K. Pratt, "Digital Image Processing", New York: Wiley, 1991.
- [19] Jagadish H. Pujar, Kiran S.Kunnur, "A novel approach for Image Restoration via Nearest Neighbour Method", *Journal of Theoretical and Applied Information Technology*, pp. 76-79, 2010.
- [20] Jagadish H. Pujar, Shambhavi D.S., "A Novel Digital Algorithm for Sobel Edge Detection", *BAIP 2010, CCIS 70*, pp. 91-95, 2010.
- [21] Jagadish H. Pujar, Pallavi S.Gurjal, "Binary Data Compression Using Medial Axis Transform Algorithm", *BAIP 2010, CCIS 70*, pp.417-419, 2010.
- [22] Frost, V.S., Stiles, J.A., Josephine, A., Shanmugan, K. S., and Holtzman, J.C., 1982. A Model for Radar Images and Its Application to Adaptive Digital Filtering of Multiplicative Noise. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. PAMI-4, No. 2, March 1982.



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