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NORMALIZED CUTS BASED SEGMENTATION OF GASTROENTROLOGY IMAGES USING VISUAL FEATURES

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Abstract: This project propose a segmentation of gastroenterology image of cancer infected stomach which is taken using Chromo endoscopy (CH).Traditional computer system segmentation do not detect the characteristics of infected region. Gastroentrology imaging is an essential tool to detect gastrointestinal cancer in patients. From the gastroenterology physician can analysis the internal organs. Initially finding the boundary of the infected area by the process called active contour or snakes. By using the various visual features like edge maps, creaseness and colour in normalised cuts segmentation framework we are segmenting the affected area in stomach. On integration of these visual features gives the best image segmentation performance resulting in high quality.
Keywords- Clustering, Cancer, Chromo endoscopy, Normalized Cuts, Gastroentrology.

I. INTRODUCTION

The field of digital image processing refers to processing digital images by means of a digital computer [1]. Note that a digital image is composed of a finite number of elements, each of which has a particular location and value [4]. These elements are referred to as picture elements, image elements, pels, and pixels. Pixel is the term most widely used to denote the elements of a digital image. Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human perception [3]. However, unlike humans, who are limited to the visual band of the electromagnetic (EM) spectrum, imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate on images generated by sources that humans are not accustomed to associating with images. These include ultrasound, electron microscopy, and computer-generated images. Thus, digital image processing compasses a wide and varied field of applications [5]. There is no general agreement among authors regarding where image processing stops and other related areas, such as image analysis and computer vision, start. Sometimes a distinction is made by defining image processing as a discipline in which both the input and output of a process are images. The processes of acquiring an image of the area containing the text, pre-processing that image, extracting or segmenting the individual characters, describing the characters in a form suitable for computer processing, and recognizing those individual characters are in the scope of what we call digital image processing. Antonio M. Lopez, Felipe Lumbreras, Joan Serrat, and Juan J. Villanueva [15] proposed a evaluation of methods for ridge and valley detection. Ridges and valleys are useful geometric features for image analysis. Different characterizations have been proposed to formalize the intuitive notion of ridge or valley. In this paper, we review their principal characterizations and propose a new one. Subsequently, we evaluate these characterizations with respect to a list of desirable properties and their purpose in the context of representative image analysis tasks. In image analysis, the ridge or valley characterizations must be evaluated with regards to their usefulness in specific applications. This paper assesses the merits of the main characterizations by testing them in several types of image analysis problems. To find the creaseness first finds it maxima and minima of the image. These maxima are connected from one level to the next, forming a subset of the so-called vertex curves. This paper put more concentration on multi local creaseness like structure tensor. Creases can be also obtained by thresholding a creaseness measure. The ridge valley detection based on vertex condition is unsatisfactory, due to the high number of irrelevant branches joining the main centerline. Some of these branches are artifacts due to the high order of the derivatives involved in the vertex condition. Inderjit S. Dhillon, Yuqiang Guan and Brian Kulis [12] proposed a Kernel kmeans, Spectral Clustering and Normalized Cuts. To identify clusters those are non-linearly separable in input space. Despite significant research, these methods have remained only loosely related. In this paper, we give an explicit theoretical connection between them. We show the generality of the weighted kernel k-means objective function, and derive the spectral clustering objective of normalized cut as a special case. Given a positive definite similarity matrix, our results lead to a novel weighted kernel k-means algorithm that monotonically decreases the normalized cut. This has important implications: eigenvector-based algorithms, which can be computationally prohibitive, are not essential for minimizing normalized cuts, various techniques, such as local search and acceleration schemes, may be used to improve the quality as well as speed of kernel k-means. Finally, we present results on several interesting data sets, including diametrical clustering of large general expression matrices and a handwriting recognition data set. Spectral clustering has emerged recently as a popular clustering method that uses eigenvectors of a matrix derived from the data. To speed up the distance computation in our weighted kernel k-means algorithm, we can adapt the pruning procedure. The k-way normalized cut problem is to minimize the links that escape a cluster relative to the total weight of the cluster. The traditional k-means objective function can be recast as a trace maximization problem of the Gram matrix for the original data. Sergio Veral, Debora Gill, Antonio Lopez and Miguel Gonzalez proposed a Multi local Creaseness Measure. Ridges and valleys are relevant image descriptors on image analysis used in several tasks of image processing and computer vision, such as centerline calculation, shape representation, and segmentation among others. The information of the Structure Tensor allows the computation of the predominant direction of change around a point in the image. Ridges of the distance map can be used to calculate the skeleton of arbitrary shapes and volumes. It is templated over the input image and the output image, although the only required template is the input image. Because of that the operator is highly discriminant. Creases have positive for ridges and negative for valleys responses. Those responses have similar value for creases of similar steepness, thus allowing the binarization of the creaseness map using a simple threshold. One of the most useful states that ridges or valleys are extream of curvature of the level curves of the landscape. The idea holds for N dimensional images, since we can always define the concept of level hyper surfaces and, thus, their extrinsic curvature. However, the fact that such definition is too local, gives rise to different problems due to the discrete nature of images.

II. PROPOSED SYSTEM

The proposed methodology is applied to the scenario of segmentation of GE images from imaging modality, CH (chromo endoscopy) from stomach. The use of multiple image features including edge maps, creaseness, and color features to further enhance the segmentation. The system uses normalized cuts (NCut) for the segmentation of GE images.

A. Active Contour

Active contour [13] model, also called snakes, is a framework for delineating an object outline from a possibly noisy 2D image. This framework attempts to minimize an energy associated to the current contour as a sum of an internal and external energy. The external energy is supposed to be minimal when the snake is at the object boundary position. The most straightforward approach consists in giving low values when the regularized gradient around the contour position reaches its peak value.The internal energy is supposed to be minimal when the snake has a shape which is supposed to be relevant considering the shape of the sought object. The most straightforward approach grants high energy to elongated contours and to bended/high curvature contours, considering the shape should be as regular and smooth as possible. The snake's model is popular in computer vision, and led to several developments in 2D and 3D. In two dimensions, the active shape model represents a discrete version of this approach, taking advantage of the point distribution model to restrict the shape range to an explicit domain learned from a training set. Snake is an energy minimizing, deformable spline influenced by constraint and image forces that pull it towards object contours. Snakes are greatly used in applications like object tracking, shape recognition, segmentation, edge detection, stereo matching.

Snakes may be understood as a special case of general technique of matching a deformable model to an image by means of energy minimization. Snake is an active model as it always minimizes its energy functional and therefore exhibits dynamic behavior. One may visualize the snake as a rubber band of arbitrary shape that is deforming with time trying to get as close as possible to the object contour. Snakes do not solve the entire problem of finding contours in images, but rather, they depend on other mechanisms like interaction with a user, interaction with some higher level image understanding process or information from image data adjacent in time or space. In general snake is placed near the object contour. It will dynamically move towards object contour by minimizing its energy iteratively. In Snakes, we use the technique of matching a deformable model to an image by means of energy minimization. A snake initialized near the target gets refined iteratively and is attracted towards the salient contour. A snake in the image can be represented as a set of n points.

$v_i = (x_i, y_i)$
(4.1)
where $i = 0 \ldots n-1$

We can write its energy function as

$$E^*_{snake} = \int_0^1 Esnake\,(v(s))\,ds = \int_0^1 (Einternal\,(v(s)) + Econ(v(s))Eimage(v(s)))ds \quad (4.2)$$

$$E_{external} = E_{image} + E_{conv} \quad (4.3)$$

where $E_{internal}$ represents the internal energy of the spline (snake) due to bending, E_{image} denotes the image forces acting on spline and E_{conv} serves as external constraint forces introduced by user. The combination of E_{image} and E_{conv} can be represented as $E_{external}$, that denote the external energy acting on the spline.

B. Internal energy

Internal Energy of the snake is

$$E_{internal} = E_{cont} + E_{curv} \quad (4.4)$$

Where E_{cont} denotes the energy of the snake contour and E_{curv} denotes the energy of the spline curvature.

$$E_{internal} = (\propto(s)|Vs(s)|^2 + \beta(s)|Vss(s)|^2/2 \quad (4.5)$$

The first order term makes the snake act like a membrane and second order term makes it act like a thin plate. Large values of α(s) will increase the internal energy of the snake as it stretches more and more, whereas small values of α(s) will make the energy function insensitive to the amount of stretch. Similarly, large values of β(s) will increase the internal energy of the snake as it develops more curves, whereas small values of β(s) will make the energy function insensitive to curves in the snake. Smaller values of both α(s) and β(s) will place fewer constraints on the size and shape of the snake.

C. Image forces
Further, E_{image} has three components:
- Lines
- Edges
- Terminations

The energies can be represented as follows:
$E_{image} = w_{line} E_{line} + w_{edge} E_{edge} + w_{term} E_{term}$ (4.6)
Adjusting the weights in the image will determine salient features in the image which will be considered by the snake.

D. Line functional
A line functional is nothing but the intensity of the image, which can be represented as,
$E_{line} = I(x, y)$ (4.7)
Depending on the sign of w_{line}, the line will be attracted to either dark lines or light lines.

E. Edge functional
1. Image gradient
Edges in the image can be found by the following energy function which will make the snake attract towards contours with large image gradients.
$E_{edge} = -\left|\nabla I(x,y)\right|^2$ (4.8)

2. Scale space
It is rather common that a snake started far from the object converges to the desired object contour. If a part of the snake finds a low energy feature, it pulls the other parts of the snake to continue to the contour. Scale Space continuation can be used in order to achieve desired results. One can allow the snake to come to equilibrium on a blurry energy edge functional and reduce the blurring as the calculation progresses. The energy functional is

$E_{edge} = \left|G\sigma * \nabla^2 I\right|^2$ (4.9)
Where $G\sigma$ is a Gaussian standard deviation σ minimum of this functional lie on zero-crossings of $G\sigma * \nabla^2 I$ which define edges in Marr- Hildreth Theory[3]. Thus the snake gets attracted towards zero-crossing constrained by its own smoothness.

3. Termination functional
Curvature of level lines [11] in a slightly smoothed image is used to detect corners and terminations in an image. Let $C(x, y) = G\sigma * I(x, y)$ be a slightly smoothed version of the image. Let $\theta = \arctan(Cy / Cx)$ be the gradient angle.
Let $n = (\cos\theta, \sin\theta)$ and $n^{\perp} = (-\sin\theta, \cos\theta)$ be unit vectors along and perpendicular to the gradient direction. The termination functional of energy can be represented as
$E_{term} = \frac{\partial\theta}{\partial n^{\perp}} = CyyCx2 - 2CxyCxCy + CxxCy2 / (Cx2 + Cy2)3/2$ (4.10)

4. Constraint energy
Some systems, including the original snakes implementation, allowed for user interaction to guide the snakes, not only in initial placement but also in their energy terms. Such constraint energy E_{con} can be used to interactively guide the snakes towards or away from particular features.

5. Advantages of active contour
Snakes have multiple advantages over classical feature attraction techniques.
- Snakes are autonomous and self-adapting in their search for a minimal energy state.
- They can be easily manipulated using external image forces.
- They can be made sensitive to image scale by incorporating Gaussian smoothing in the image energy function.
- They can be used to track dynamic objects in temporal as well as the spatial dimensions.

F. K-Means Clustering
K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The points are clustered around centroids μi for all i = 1: k which is obtained by minimizing the objective.
$V = \sum_{i=1}^{k} \sum_{Xj \epsilon Si} (Xj - \mu i)^2$ (4.11)
Where there are k clusters Si, i = 1, 2,….k and μi is the centroid or mean point of all the points xj€Si. As a part of this project, an iterative version of the algorithm was implemented.

G. Algorithm
The algorithm takes a 2 dimensional image as input. Various steps in the algorithm are as follows:
1. Compute the intensity distribution (also called the histogram) of the intensities.
2. Initialize the centroid with k random intensities.
3. Repeat the following steps until the cluster labels of the image do not change anymore.
4. Cluster the points based on distance of their intensities from the centroid intensities.
5. Compute the new centroid for each of the clusters.

H. Normalised Cuts
Let G = (V;E) be an undirected weighted graph [10] with a set of vertices V and a set of unordered pairs of edges E, where each (i; j) 2 E has an associated weight wij . The weight, wij indicates the strength of the connection, or edges, between node i and j. A strong connection between node i and j would have a high wij value, and vice versa. A strong connection between groups of nodes generally indicates that these nodes are very similar and belong as one cluster.
The graph G can be segmented into two disjoint subsets of the graph, G1 and G2, if we remove the connecting edges between the sets G1 and G2. In graph theory, the removal of these edges, or a cut, is a partition of graph vertices into two disjoint subsets. The cut of a weighted graph G into two disjoint subsets G1 and G2 is defined as:

Cut (G1, G2) = $\sum_{i \in G1, j \in G2} wij$ (4.12)

Generally, two different graph clusters with weak connections between them will have a small cut value if we partition them. Usually, the goal of segmentation is to find a set of clusters that correspond to low cut values. The degree of a vertex, or 3 nodes, in a weighted graph is the total weight of the edges incident to the node. Let d_i be the degree of a node i in the graph. Then:

$d_i = \sum_j wij$ (4.13)

The volume of a subset G1 of a weighted graph represents how dense the subset G1 is in terms of its edge weights. In general, a high volume value indicates that the connections within the subset are strong. Let vol (G1) be the volume of the subset G1

vol(G1) = $\sum_{i \in G1} di$ (4.14)

Normalized Cut is given as:

Ncut (G1, G2) = $\frac{\text{cut (G1,G2)}}{\text{vol (G1)}} + \frac{\text{cut (G1,G2)}}{\text{vol (G2)}}$ (4.15)

The Normalized Cut Algorithm minimizes the Normalized Cut (NCut) criterion.

In general, for two different graph clusters, strong internal connections within the clusters indicate similar grouped nodes and weak connections between these clusters indicate that these two clusters are different. Intuitively, by minimizing the normalized cut criterion for groups G1 and G2, we find a cut such that the connections between the newly partitioned groups are weak and that the nodes are evenly distributed so that the internal connections for the new groups are both evenly strong. By minimizing the normalized cut criterion for G1 and G2, we try to find new balanced partitions that give a small cut value and strong internal connections for both the partitions at the same time. In solving this minimization problem in , let D be an N x N diagonal matrix with degree d on its diagonal. Let W be an N x N symmetrical matrix with W(i; j) = wij . The W matrix is known as the affinity matrix. Nodes with high affinity will have high weight values, while nodes with low affinity will have low weight values. The NCut criterion in can be solved by solving the following generalized eigen value system:

(D - W)x = D_x (4.16)

The second smallest eigenvector of the generalized eigen system is the real valued solution to the NCut problem.

1. The Recursive Two-way NCut Algorithm

Let the image we are trying to segment be the set of pixels I.

1. Given the set of features, construct a weighted graph G = (V;E), compute the edge weights W(i; j). In this application, the image I is the graph, and the pixels are the nodes. Calculate the corresponding D matrix.
2. Solve (D-W)x = Dx for eigenvectors with the smallest eigenvalues.
3. Select the eigenvector with the second smallest eigenvalue to bipartition the graph by finding the splitting point such that the NCut criterion is minimized.
4. Decide if the current partition should be subdivided by checking the stability of the cut, and make sure that NCut is below the prespecified threshold.
5. Recursively repartition the segmented parts if necessary given the number of segments specified by the user.

2. Constructing the Affinity Matrix

We need to define the edge weights wij prior to starting the recursive two-way NCut Algorithm. In the original NCut algorithm, each entry wij in the affinity matrix W is constructed as follows

$$w_{ij} = e^{-\| F(i) - F(j)\|2} / \sigma_F * \begin{cases} e^{-\| X(i) - X(j)\|2} / \sigma_x & \text{if } \| X(i) - X(j)\|^2 < R \\ 0 & \text{otherwise} \end{cases} \quad (4.17)$$

where

- X(i) is the spatial location of node i.
- F(i) is a feature vector based on intensity, color, or texture information of node i.
- σF;σX are feature and spatial tuning parameters respectively.

For a black and white image, the feature (sometimes called intensity) of a pixel i, F(i), takes values between 0 (black) and 255 (white). Note that, the weight wij = 0 for any pair of pixels i and j that are lying more than R pixels apart.

III. SIMULATION RESULTS AND DISCUSSIONS

A. Input image

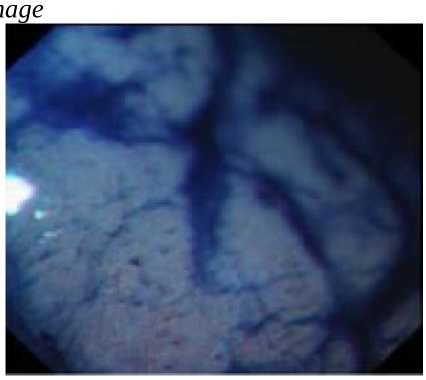

Figure 3.1 Input Image

Figure 3.1 shows the input image of cancer affected stomach. The size of the original image is 169X159. Then the image is resized into 512x512. This original image is getting from the biopsy using the chromoendoscopy technique.

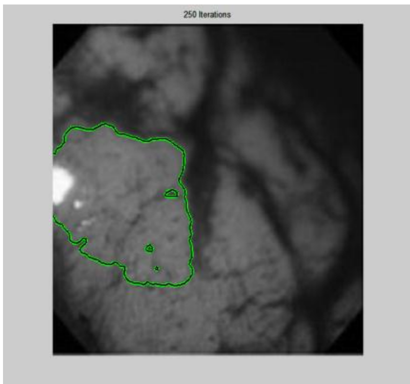

Figure 3.2 140 Iteration process

Figure 3.2 shows the image under active contour of 140 iteration. Active contour is initially used to find the boundary of the infected area.

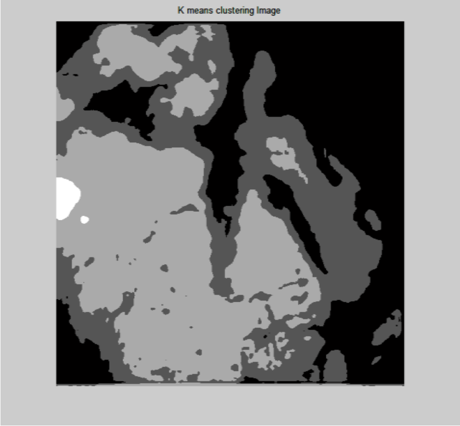

Figure 3.3 K-means clustering

Figure 3.3 shows the clustering output using k-means. This k-means clustering is based on the divisive clustering. Here k is taken as 4 and dividing iteratively using the centroid calculation.

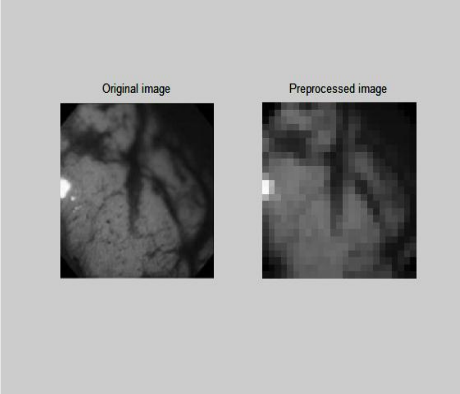

Figure 3.4 Original image vs preprocessed image

Figure 3.4 shows the comparision between the original image and pre-processed image. Original image is processed to avoid out of memory error.

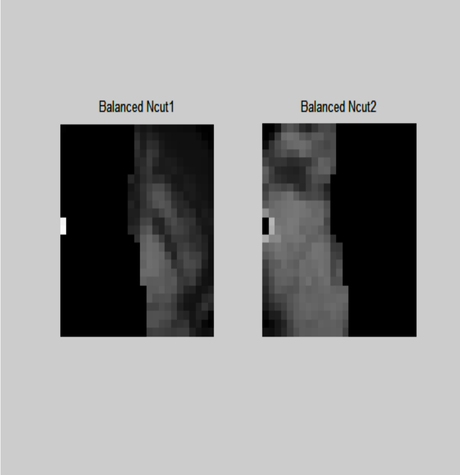

Figure 3.5 Balanced Ncuts

Figure 3.5 shows the balanced Ncuts 1 image and balanced Ncuts 2 image. This segment the image into two balanced image.

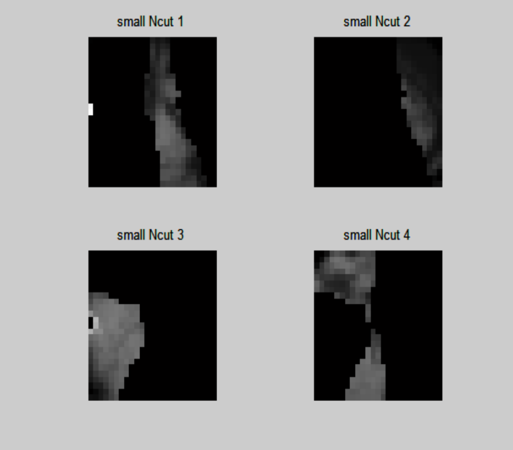

Figure 3.6 Second level partitioning

Figure 3.6 shows the small Ncuts image. In second level partitioning the image is divided into four small Ncuts images or four sub graphs.

Figure 3.7 Third level bi-partioning

Figure 3.7 shows the third level bi-partioning image.This divides the image into eight subgraphs.

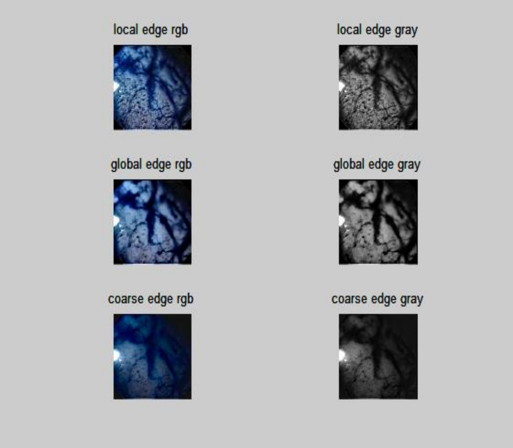

Figure 3.8 Edge map

Figure 3.8 shows the edge mapping of an image. It maps the edges of an image at three levels. They are fine stage, medium stage, and coarse stage. These variations are based on the richness of the texture.

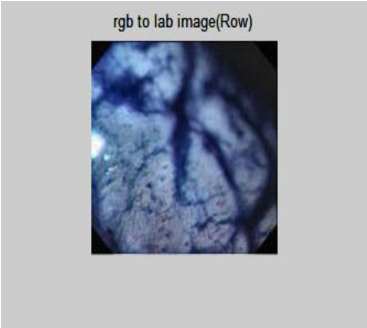

Figure 3.9 RGB to lab image in row

Figure 3.9 shows the rgb to lab image in rows. This gets an image in the CIELAB colour. Space and tone maps it according to the parameters.

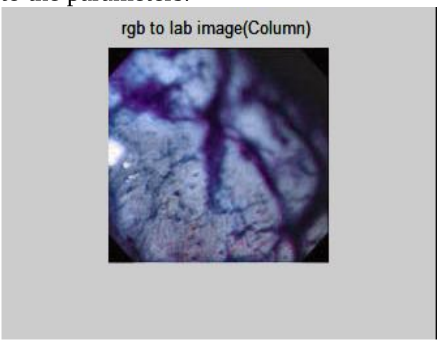

Figure 3.10 RGB to lab image in coloumn

Figure 3.10 shows the rgb to lab image in column. This gets an image in the CIELAB color. Space and tone maps it according to the parameters.

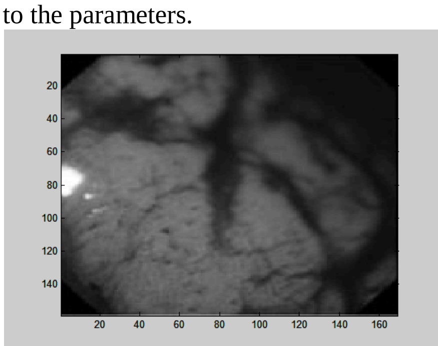

Figure 3.11 Luminance image

Figure 3.11 shows the luminance image. It describes the CH image with luminance component. Luminance image is usually in light color. Color extracting feature is done by using the color space L*U*V*.

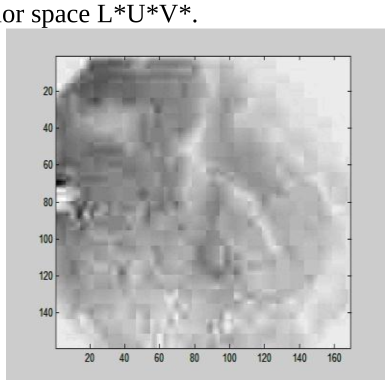

Figure 3.12 Chrominance image

Figure 3.12 shows the chrominance image. It describes the CH image with luminance component. Chrominance image is usually in dark color. Color extracting feature is done by using the color space L*U*V* which is defined by the CIE (Commission Internationale de Eclairage).

Figure 3.13 Creaseness

Figure 3.13 shows the creaseness of image. This describes creaseness of an image at three stages namely fine, medium, coarse stage respectively. Creaseness is determined using the special descriptor named as multilocal level set extrinsic curvature with enhancement by structure tensor (MLSEC-ST) operator.

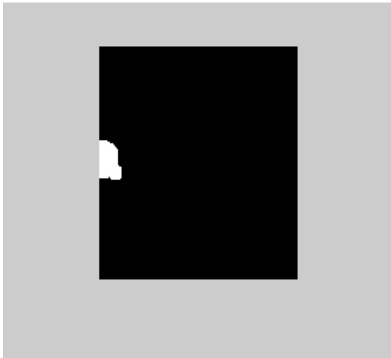

Figure 3.14 Final edge of cancer

Figure 3.14 shows the area of cancer in the image. The white region describes the affected area in stomach. This is done by combining the visual features with the normalized cuts algorithm.

IV. CONCLUSION

Image segmentation is an essential component of CAD systems for diagnosis of cancer in GE imaging. It is a challenging problem given the dynamics of imaging conditions and imaging modalities that add to the difficulty of computer-vision-based tasks for assisted decision making. A wide variety of methods are available that can be used for segmentation of GE images. However, we chose NCut given their robustness to noise, ability to avoid over segmentation for high textured images due to a global optimization criterion, and their ability to accommodate various visual features based on the nature/contents of the images. We have proposed the novel integration of creaseness features in NCut image segmentation framework to improve the quality of the resulting image segments as compared to the usage of state-of-the-art multiscale edgemaps. The novel methodology is motivated by the ability of creaseness to enhance directional gradients in the images while suppressing the local texture in the images. In GE images, the directional gradient is typically found around the clinically relevant region in the image; thus, we have a good chance of getting very meaningful segmentation when creaseness is integrated in

NCut framework. In future the performance of three popular segmentation algorithms when applied to two distinct in-body imaging scenarios: chromoendoscopy and narrow-band imaging. Observation shows that the model-based algorithm did not perform well, when compared to its segmentation by clustering alternatives. Normalized cuts obtained the best performance although future work hints that texture similarity should be further explored in order to increase segmentation performance in this type of scenarios.

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