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Liver And Tumor Segmentation Using Live Wire, Active Appearance Model And Graph Cut Method

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Abstract
Graph Cuts methods represent an established methodology and have been previously applied for liver segmentation purposes; instead, the Geodesic Graph-Cut technique solutions allow avoiding local minima, providing numerical robustness and do not use any shape-prior characteristics that would constrain too strongly recoverable shapes. The Geodesic Graph-cut algorithm produces also better segmentation results than other fully automatic methods found in literature in both terms of accuracy and time processing. This method also effectively combines the Active Appearance Model, Live Wire and Graph Cut ideas to exploit their complementary strengths. It consists of three main parts: model building, initialization, and delineation. For the initialization (recognition) part, employ a pseudo strategy and segment the organs slice by slice via the OAAM method. The purpose of initialization is to provide rough object localization and shape constraints for a latter GC method, which will produce refined delineation.

Keywords: Active Appearance Model, Graph cut method, Live Wire method.

I.INTRODUCTION

Magnetic resonance imaging is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. A three-dimensional active appearance model method for analysis of volumetric cardiac images and temporal image sequences was presented and its performance demonstrated in two substantially different cardiac imaging modality case studies.It has several advantages over other imaging techniques.

MRI can provide three-dimensional data with high contrast between soft tissues. However, the amount of data is far too much for manual interpretation and analysis, and this has been one of the biggest problems in the effective use of MRI. The goal of MR image segmentation is to accurately identify the principal tissue structures in these image volumes. There are several typical MRI segmentation approaches as follows:

1. Threshold techniques where the classification of each pixel depends on its own information such as intensity and color information. Those techniques are efficient when the histograms of objects and background are clearly separated.
2. Edge-based methods are focused on detecting contour. They fail when the image is blurry or too complex to identify a given border.
3. Region-based segmentation in which the concept of extracting features (similar texture, intensity levels, homogeneity or sharpness) from a pixel and its neighbors is exploited to derive relevant information for each pixel.
4. Cooperative hierarchical computation approach use pyramid structures to associate the image properties to an array of father nodes, selecting iteratively the point that average or associate to a certain image value.
5. Statistical approaches this type of method labels pixels according to probability values, which are determined based on the intensity distribution of the image. With a suitable assumption about the distribution, statistical techniques attempt to solve the problem of estimating the associated class label, given only the intensity for each pixel. Such an estimation problem is necessarily formulated from an established criterion.
6. ANN image segmentation techniques originated from clustering algorithms and pattern recognition methods. They usually aim to develop unsupervised segmentation algorithms. Several brain MRI segmentation techniques using neural networks are reviewed in literature. The most famous unsupervised approach using ANN, the self-organizing feature maps (SOFM), developed by Kohonen is a strong candidate for continuous valued unsupervised pattern recognition. The algorithm includes spatial constraints by using a Markov Random Field (MRF) model. Many researchers have applied the MRF to model

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the spatial constraints in supervised and semi-supervised segmentation algorithms.

Liver cancer is one of the most wide-spread malignant diseases world-wide and a partial hepatectomy is often the only curative treatment for patients. As liver disease is one of the most common internal malignancies and also one of the leading death causes, liver intervention becomes one of the most demanding fields in surgery. The treatment of malignant liver diseases targets at the complete destruction or removal of all tumors together with a sufficient safety free margin, at the same time life-critical anatomical structures must be saved. Liver transplantation, the replacement of a diseased liver with a healthy liver allograft, has emerged in recent decades as a critical surgical option for patients with end stage liver disease and acute liver failure. It is also one of the most expensive treatments in modern medicine. Numerous anastomoses and sutures, and many disconnections and reconnections of abdominal and hepatic tissue, must be made for the transplant to succeed. An intra-operative image guided system would greatly facilitate this procedure for two reasons: 1. Radical resection would leave insufficient liver mass, leading to liver failure; 2. the volume of operative blood loss significantly affects postoperative mortality and morbidity Liver cancer is one of the most fatal causes of death worldwide. Liver surgery for the treatment of hepatic tumors, including transplantation, requires information of the liver volume. Volumetry of the liver is usually performed by manual tracing of the liver boundary on CT images. There is a large variation of liver sizes between patients and the nearby organs have very similar intensity values to the liver. Also, the partial volume effect causes the liver boundary to be ambiguous.

The Liver cancer is also one of the leading death causes. Currently, the confirmed diagnosis used widely for the liver cancer is needle biopsy. The needle biopsy, however, is an invasive technique and generally not recommended People diagnosed with liver cancer still present a low survival rate. It is among the most frequent types of cancerous diseases, showing responsible for the deaths of 600,000 patients worldwide in 2001 alone. The incidence of liver metastases is even higher, as many common cancer types, like colorectal, lung and breast cancer, tend to metastasize into the liver. Indeed in 2002, 1 million patients in the world were diagnosed with a primarily liver cancer and more than 60% did not survive. A space within the skull is covered by the brain tumor which causes the disturbance of normal brain activity. It can increase pressure in the brain, shift the brain or push it against the skull, and/or invade and damage nerves and healthy brain tissue. The location of a brain tumor influences the type of symptoms that occur. Identifying the presence of a brain tumor is the first step in determining a course of treatment. Identification of a brain tumor generally involves a neurological examination, brain scans, and/or an analysis of the brain tissue. Doctors use the diagnostic information to classify the tumor from the least aggressive (benign) to the most aggressive (malignant). Identifying the type of tumor helps doctors determine the most appropriate course of treatment.

The structure tensor has been introduced for such texture analysis as a fast local computation providing a measure of the presence of edges and their orientation. Lizard scales and rock are of similar intensity: For example, diffusion tensor MRI may be represented in this manner from the direction of water diffusion at each pixel. In this case, brain structures such as nerve bundles comprise regions of similarly oriented tensors as water diffuses along the fibers. Various tensor segmentation methods have been proposed including the recent work focusing on variational techniques such as active contours. The basic technique involves iteratively minimizing an energy defined over the statistics of the regions, with lower energies corresponding to better separated regions. A standard variational approach is to approximate the regions as having Gaussian distributions. The energy is defined as some measure of the similarity between two Gaussian distributions, e.g. the log-likelihood ratio, and segmentation proceeds to separate those distributions with active contours.

Generally the requirements of Image Segmentation algorithms are:

1. It should be based on weighted distance functions (geodesics), thereby solving a first order geometric Hamilton-Jacobi equation in computationally optimal linear time. This makes the proposed framework natural for user-interactive processing of images and videos.

2. It should produce very good, state-of-the-art results, with very few user provide scribbles and very simple attributes defining the weights in the distance computation. Rough scribbles are often used for still images (one for the foreground and one for the

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background) and scribble one frame every 70 or so for videos.

3. It should apply to a large class of natural data, and since it avoids off-line learning, it is not limited to pre-observed and classified classes and to the availability of ground-truth and hand segmented data.

4. It should handle dynamic background in video as well as crossing objects of interest.

5. The framework should be general so that additional attributes can be naturally included in the weights for the geodesic distances if so required for a particular type of data.

II.MATERIALS AND METHODS

Guillermo Sapiro.G. et al. [1] reviewed a geodesic framework for fast interactive image and video segmentation and matting which is used for interactive liver and tumor image segmentation. The technique is based on the optimal, linear time, computation of weighted geodesic distances to the user-provided scribbles, from which the whole data is automatically segmented. The weights are based on spatial and/or temporal gradients, without explicit optical flow or any advanced and often computationally expensive feature detectors. These could be naturally added to the proposed framework as well if desired, in the form of weights in the geodesic distances. A localized refinement step follows this fast segmentation in order to accurately compute the corresponding matte function. Additional constraints into the distance definition permit to efficiently handle occlusions such as people or objects crossing each other in a video sequence. The presentation of the framework is complemented with numerous and diverse examples, including extraction of moving foreground from dynamic background, and comparisons with the recent literature. With the help of Geodesics-based algorithm for natural image and video segmentation and matting, narrow band trimap is quickly generated from a few scribbles. Objects are handled well that cross each other in video temporal domain. But it produces poor performance when the distributions overlap and there is no regularization term in the model.

Malcolm.J. et al. [2] reviewed the Graph cut approach to image segmentation in tensor space which involved Segmentation of tensor valued images by natural Riemannian structure of the tensor. The Riemannian nature of the tensor space is explicitly taken into account by first mapping the data to a Euclidean space where nonparametric kernel density estimates of the regional distributions may be calculated from user initialized regions. These distributions are then used as regional priors in calculating graph edge weights. Hence this approach utilizes the true variation of the tensor data by respecting its Riemannian structure in calculating distances when forming probability distributions. Further, the non-parametric model generalizes to arbitrary tensor distribution unlike the Gaussian assumption made in previous works. Casting the segmentation problem in a graph cut framework yields a segmentation robust with respect to initialization on the data tested.

The Technique captures true variation of object and background. But the Method may fail when two textures differ only in scale and it does not give satisfactory performance as GVF technique.

Protiere.A. et al. [3] reviewed the Interactive image segmentation approach via adaptive weighted distances which is an interactive algorithm for soft image segmentation. The user first roughly scribbles different regions of interest, and from them, the whole image is automatically segmented. This soft segmentation is obtained via fast, linear complexity computation of weighted distances to the user-provided scribbles. The adaptive weights are obtained from a series of Gabor filters, and are automatically computed according to the ability of each single filter to discriminate between the selected regions of interest. In order to address the above mentioned key challenges (work fast and for a large class of images), an interactive image segmentation approach was presented inspired by the colorization work where the goal is to add color (or other special effects) to a given mono-chromatic image. In this work, a series of color scribbles were provided on a luminance-only image, and then use geodesic distances computed from the same luminance channel to compute the probability for a pixel to be assigned to a particular scribble.

A semi-automatic algorithm was proposed for the segmentation of natural images in which the weights to be used for the geodesic distance were first generalized, going beyond simple gradients, and thereby permitting to handle significantly more complicated data. The weight provided by the gradient is replaced by weights automatically learned and adapted to the image. Then the distances were computed from every pixel to the scribbles (region labels provided by the user), keeping the low computational cost of the geodesic computation.

Finally, from these weighted distances, the probability of a pixel to belong to the region corresponding to every user-provided scribble. The use of fast geodesic computations is a very interesting way to perform semi-automatic segmentation starting from user provided labels. In its original form, this method assumes that the gradient of the intensity (or color) is low inside the region of interest and high at the boundaries. Although there are a lot of images where this assumption is reasonable, it obviously fails for example for images containing textures. While preserving the general idea of obtaining a soft segmentation by geodesic propagation of user-provided labels, different weights were used in defining the distance. In other words, the term representing the gradient of the luminance channel was replaced by a more elaborated weighting function, and then still derives the soft segmentation via the fast geodesic computation.

This technique provides automatic weighting of different channels which is adaptable to wide range of images. Also this technique provides greater time linearity and better Image labeling. But it has greater computational complexity and there is no proper definition of appropriate weights and it does not fit image modality.

Schoenemann.T. et al. [4] reviewed the Curvature regularity for region-based image segmentation and inpainting which is a linear programming relaxation technique. This minimization approach was used for region-based image segmentation independent of initialization. To minimize such energies, an integer linear program was formulated which jointly estimates regions and their boundaries. Curvature regularity was imposed by respective costs on pairs of adjacent boundary segments. By solving the associated linear programming relaxation and thresholding, the solution one obtains is an approximate solution to the original integer problem. This was the first approach to impose curvature regularity in region-based formulations in a manner that is independent of initialization and allows computing a bound on the optimal energy. In a variety of experiments on segmentation and inpainting, the advantages of higher-order regularity are demonstrated. Moreover, the optimality gap is smaller than 2% of the global optimum.

The key idea is to cast the problem of region-segmentation with curvature regularity as an integer linear program (ILP). By solving its LP-relaxation and thresholding the solution a solution is obtained to the original integer problem. In addition, the method readily extends to the problem of inpainting. For contour edge-based segmentation methods researchers have successfully developed algorithms to optimally impose curvature regularity using shortest path approaches or ratio cycle formulations on a graph representing the product space of image pixels and tangent angles. In the region based settings considered, curvature is usually handled by local evolution methods. The only exception is the inpainting approach of Masnou and Morel who can optimize the L1-norm of the curvature in the absence of data terms using dynamic programming.

The LP-relaxation approach was developed to minimize curvature in region-based settings. In contrast, it allows imposing arbitrary functions of curvature and arbitrary data terms. The algorithmic formulation is based on the concepts of cell complexes and surface continuation constraints which have been pioneered by Sullivan and Grady in the context of 3D-surface completion. To this end, the problem is formulated as an integer linear program and its LP-relaxation is solved.This technique produces integral solution to region variable thresholding and the results are close to global optimum. But the approach was not suitable for moderate image resolutions and it consumes larger running time.

Talbot.H. et al. [5] reviewed the Power watersheds approach which is an image segmentation framework extending graph cuts, random walker and optimal spanning forest. Viewing an image as a weighted graph, these algorithms can be expressed by means of a common energy function with differing choices of a parameter q acting as an exponent on the differences between neighboring nodes. Introducing a new parameter p that fixes a power for the edge weights allows us to also include the optimal spanning forest algorithm for watersheds in this same framework. Placing the watershed algorithm in this energy minimization framework also opens new possibilities for using unary terms in traditional watershed segmentation and using watersheds to optimize more general models of use in application beyond image segmentation.

The algorithm solves the energy minimization problem associated with the power watersheds and has the speed of standard watersheds but outperforms all of the other algorithms on our benchmark segmentation tests. Placing watersheds in the same framework as graph cuts, random walker and shortest paths allows us to easily incorporate unary terms into conventional watershed segmentation. By placing the watershed algorithm in the same

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generalized framework as graph cuts, random walker and shortest paths, it is possible to take advantage of the vast literature on improving watershed segmentation to also improve these other segmentation approaches. By incorporating unary terms, watersheds are pushed beyond image segmentation into the area of general energy minimization algorithms which could be applied to any number of applications for which graph and MRF models have become standard.

A general framework encompassing graph cuts, random walker, shortest-path segmentation and watersheds allowed to define a new family of optimal spanning forest for watershed segmentation algorithms using different exponents. The algorithm for computes power watershed and showed that the power watershed with q = 2 retains the speed of the MSF algorithm while producing improved segmentations. In addition to providing a new image segmentation algorithm, this work also showed how unary terms could be employed with a standard watershed algorithm to improve the segmentation performance. Viewed as energy minimization algorithms, graph cuts, random walker and shortest paths have found many different applications in the computer vision field that go beyond image segmentation, such as stereo correspondence, optical flow and image restoration.

III.METHODOLOGY

To segment body organs, effectively combine the LW, AAM, and GC methods and construct a new technique which is named as GC–OAAM. The aim of the proposed method is to combine the complementary strengths of these individual methods (LW, AAM, GC) to arrive at a more powerful hybrid strategy to overcome the weakness of the component methods. Let see about these individual methods.

The boundary-based segmentation strategies have two specific aims:

1) To provide as complete a control as possible to the user on the segmentation process while it is being executed and

2) To minimize the user involvement.

The total user's time required for segmentation, without compromising the precision and accuracy of segmentation. This strategy in these boundary-based segmentation methods has been to actively exploit the superior abilities of human operators (compared to computer algorithms) in object recognition and the superior abilities of computer algorithms (compared to human operators) in object delineation.

Falcao and Udupa developed a method that determines object boundary information from orthogonal slices of a volume segmented by a user. This technique allows the user to segment a minimal number of slices, reducing the total segmentation time.

The user-steered 2-D segmentation method [9] allows the user to select three seed points. After selection, Live Wire is used to generate an initial frame and then "spokes." After the spokes are found, a gap filling algorithm is used to close the space between spokes.

The Live Wire method stands out among the class of user-interactive image segmentation tools. The user clicks on an edge of the object with the mouse, defining a "seed point". The user then moves the cursor to some other portion of the object's edge. The pixel that lies under the cursor is called the "free point". As the free point moves, a wire connecting the seed point and the free point automatically snaps to the edge.

While the algorithm does do significant automatic segmentation (by snapping to the edge), the user maintains complete control in that he or she can adjust the location of the free pixel if the algorithm fails to find the correct boundary. The Live Wire has proven to be very powerful and is widely used because of its high degree of user-interactivity. This is because automatic segmentation is still an unsolved problem and many datasets still require expert knowledge from users.

A drawback of this method is that the speed of optimal path computation depends on image size. On modestly powered computers, for images of even modest size, some sluggishness appears in user interaction, which reduces the overall segmentation efficiency. In this work, this problem is solved by exploiting some known properties of graphs to avoid unnecessary minimum-cost path computation during segmentation. In this project, user steered segmentation paradigms, [9] referred to as live wire and live lane has used to segment three-dimensional (3-D) object boundaries in a slice-by-slice fashion.

An Active Appearance Model (AAM) is a computer vision algorithm for matching a statistical model of object shape and appearance to a new image. They are built during a training phase. A set of images,

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together with coordinates of landmarks that appear in all of the images, is provided to the training supervisor.

The model was first introduced by Edwards, Cootes and Taylor[6] in the context of face analysis, 1998. They further described the approach as a general method in computer vision at the European Conference on Computer Vision in the same year. The approach is widely used for matching and tracking faces and for medical image interpretation.

The algorithm uses the difference between the current estimate of appearance and the target image to drive an optimization process. By taking advantage of the least squares techniques, it can match to new images very swiftly. It is related to the active shape model (ASM) [7].
One disadvantage of ASM is that it only uses shape constraints, and does not take advantage of all the available information – the texture across the target object. This can be modeled using an AAM.
PCA is used to find the mean shape and main variations of the training data to the mean shape[6]. After finding the Shape Model, all training data objects are deformed to the main shape, and the pixels converted to vectors. Then PCA is used to find the mean appearance (intensities), and variances of the appearance in the training set. Both the Shape and Appearance Model are combined with PCA to one AAM-model.

PCA is a technique that is useful for the compression and classification of data. The purpose is to reduce the dimensionality of the data set(sample) finding a new set of variables smaller than the original set of variables, nonetheless retains the most of the sample's information.
By information we mean the variation present in the sample, given by correlation between the original variables, called principal component's(PCs) are uncorrelated, are ordered by the fraction of total information each retains.
PCA is a powerful tool for analyzing data. The main advantage of PCA is that once you have found these patterns in the data, and you compress the data, ie., by reducing the number of dimensions, without much loss of information. This technique used in image compression.
As applied in the field of computer vision, graph cuts can be employed to efficiently solve a wide variety of low-level computer vision problems, such as image smoothing, the stereo correspondence problem, and many other computer vision problems that can be formulated in terms of energy minimization. Such energy minimization problems [14] can be reduced to instances of the maximum flow problem in a graph .Under most formulations of such problems in computer vision, the minimum energy solution corresponds to the maximum a posteriori estimate of a solution.
Although many computer vision algorithms involve cutting a graph (e.g., normalized cuts), the term "graph cuts" is applied specifically to those models which employ a max-flow/min-cut optimization [4]."Binary" problems (such as denoising a binary image) can be solved exactly using this approach; problems where pixels can be labeled with more than two different labels (such as stereo correspondence, or denoising of a grayscale image) cannot be solved exactly, but solutions produced are usually near the global optimum.
By applying the graph cut technique, a wide variety of low-level computer vision problems, such as image smoothing and many other computer vision problems and the stereo correspondence problem, can be solved in terms of energy minimization. This approach can solve binary problems exactly: But, problems where pixels can be labeled with more than two different labels cannot be solved exactly, but there is the optimum solution to the problem.
In the graph cut technique we represent the image in the form of graphs. That means containing nodes and vertices like a graph. So here we represent the each pixel as a node and the distance between those nodes as the edges. In graph theory, a cut is a partition of the nodes that divides the graph into two disjoint subsets. The set of cuts of the cut is the set of edges whose ending points are in different subsets of the divided region.
If edges are in its cut-set then they are said to be crossing the cut. In an un-weighted undirected graph, we can say that the weight or size of a cut is the number of edges that are crossing the cut in an image. And in the case of a weighted graph, it is defined as the sum of the weights of all the edges crossing the cut. The basic cuts in the graph theory are minimum cut and maximum cut.
In the minimum cut technique the size of the cut is not larger than the size of the any other cut. The figure showed in the below shows a minimum cut: Here the cut size is 2, and there is no cut of size 1 because the graph is bridgeless.

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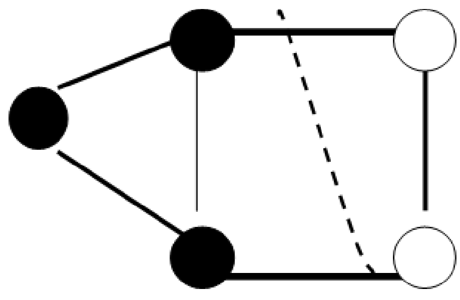

Fig. 1. Minimum Cut

A cut is maximum if the size of the cut is not smaller than the size of any other cut in the image.

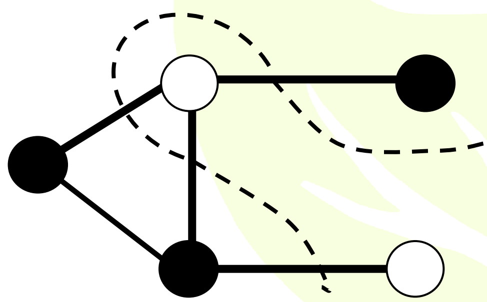

Fig.2. Maximum Cut

Wu and Leahy proposed a clustering method based on this minimum cut criterion. In the minimum curt technique we need to segment each and every pixel of an image. That means in this technique we need to cut each pixel in an image even if those pixels are similar with respect to color or intensity or texture. So in this minimum cut technique we couldn't get a better segmented image when compared to the other techniques so here we use the normalized cut method to segment the image.

In particular, they want to partition a graph into k-sub graphs such that the maximum cut across the subgroups is minimized. This problem can be efficiently solved by recursively finding the minimum cuts that bisect the existing segments. This globally optimal criterion can be used to produce good segmentation on some of the images. The minimum cut criteria favors cutting small sets of isolated nodes in the graph. Assuming the edge weights is inversely proportional to the distance between the two nodes. In fact, any cut those partitions out individual nodes on the right half will have smaller cut value than the cut that partitions the nodes into the left and right halves.

The normalized cut method was proposed by J. Malik and J. Shi. In their view, the image segmentation problem can be seen as a graph theory problem. Graph theory is an interesting math topic which models math problems into edges and vertexes. Here, representing the each pixel as a vertex or node and the distance between those nodes as the edges. This model could be used for coloring problems. Each edge in the model could contain a value, which could be used as flow of it. This kind of graph is called "weighted graph.

LW is a user-steered 2-D segmentation method in which the user provides recognition help and in which the algorithm performs optimal delineation. The main limitation of LW stems from the recognition process, wherein the anchor points are to be selected on the boundary by a human operator.

Active Appearance Model:

AAM suffers from many difficulties in practical applications. These difficulties are mainly embodied in three aspects: the low efficiency in real-time systems, the less discrimination for recognition and segmentation systems, and the lack of robustness under inconstant circumstances. These obstacles greatly restrict the application of AAM. The specific shape and appearance information on the object in a given image is difficult to account for in these methods.

GC methods have the ability to compute globally optimal solutions (in the two-label case) and can enforce piecewise smoothness. However, they are interactive methods, requiring labeling of the source and sink seeds by a human operator.

The proposed segmentation methodology is different from the methods reported in the literature by the following considerations: 1) The strategy proposed is a 3-D technique; 2) it does not need registration of shapes and 3) to the best of our knowledge, GC–OAMM is the only method that simultaneously combines the rich statistical shape and appearance information in the AAM as well as the effective boundary-oriented delineation capability of LW and the globally optimal delineation capability of the GC method.

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The proposed GC – OAAM method consists of two phases:
1) Training Phase and
2) Segmentation Phase.

Fig.2. presents the Flowchart of the proposed GC–OAMM system. In the training phase, an AAM is constructed, and the LW boundary cost function and GC parameters are estimated. The segmentation phase consists of two main steps: recognition or initialization and delineation.

In the recognition step, a pseudo-3-D initialization strategy is employed in which the pose of the organs is estimated slice by slice via a object OAAM method. A further refinement may be needed to adjust the initialization of improperly initialized slices. The pseudo-3-D initialization strategy is motivated by two reasons.

First, 3-D initialization is difficult and has computational drawbacks; the proposed method is much faster. Second, combining the AAM and LW in a 3-D manner is challenging. Indeed, the pseudo-3-D method offers fast initialization, and its performance is comparable to the fully 3-D AAM initialization method. Finally, for the delineation part, the object shape information generated from the initialization step is integrated into the GC cost computation. Let see about the concepts, preliminary steps and important equations applied in the proposed method.

Before building the model, the top and bottom slices of each organ are first manually identified. Then, linear interpolation is applied to generate the same number of slices for the organ in every training image. This is for establishing anatomical correspondences. 2-D OAAM models are then constructed for each slice level from the images in the training set. The LW cost function and GC parameters are also estimated in this stage.

In the mathematical field of numerical analysis, interpolation is a method of constructing new data points within the range of a discrete set of known data points. In engineering and science, one often has a number of data points, obtained by sampling or experimentation, which represent the values of a function for a limited number of values of the independent variable. It is often required to interpolate (i.e. estimate) the value of that function for an intermediate value of the independent variable. This may be achieved by curve fitting or regression analysis.

Suppose the formula for some given function is known, but too complex to evaluate efficiently. A few known data points from the original function can be used to create an interpolation based on a simpler function. Of course, when a simple function is used to estimate data points from the original, interpolation errors are usually present; however, depending on the problem domain and the interpolation method used, the gain in simplicity may be of greater value than the resultant loss in accuracy.

The interpolation methods are:
1.Piecewise constant interpolation
2.Linear interpolation
3.Polynomial interpolation
4.Spline interpolation

Linear interpolation is a method of curve fitting using linear polynomials. Lerp is an abbreviation for linear interpolation, which can also be used as a verb. In this project, linear interpolation is used to generate the same number of slices for the organ in every training image.

Although semiautomatic or automatic methods are also available for annotating organs because of its simplicity, generality, and efficiency, manual land marking is still in use in clinical research. Therefore, manual land marking is used to annotate organs' shape. In manual land marking, trained operators identify prominent landmarks on each shape visually on displayed slices. We assessed a semiautomatic land marking method, which is called equal-space land marking [6] to show that there is a strong correlation between the shapes encoded by the manual and semi automated land marking methods.

Since we treat shape as an infinite point set in principle, it can be assumed that the shape of an object is captured by a finite subset of a sufficient number of its points. Therefore, different numbers of landmarks are used for different objects based on their size. Since there is a vast amount of literature on the analysis of effects of distribution of landmarks on model building and segmentation results, we avoid repeating these experiments, but we validate manual land marking by the equal-space labeling method.

Once the landmarks are specified, the standard AAM method [6], [7] is used for constructing the model. The model includes both shape and texture information. Suppose M_j represents the AAM model for slice level and the number of slice levels is , then the complete model M can be represented as M = (M_1, M_2, M_3,…..

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M_n). Similar to the oriented active shape model method [16], an oriented boundary cost function is devised for each organ included in the model M as per the LW method [9]. Following the original terminology and notation in [9], let define a boundary element (bel) as an oriented edge between two pixels with values 1 and 0. For a given image slice, a bel will be represented as an ordered pair (p,q) of four adjacent pixels, where is inside the object of four adjacent pixels, where p is inside the object (pixel value 1) and q is outside (pixel value 0), as illustrated in Fig. 3.2. Every pixel edge of as constituting two potential bels (p,q) and (p,q) and possibly assign different cost values to them.

IV.RESULTS AND DISCUSSION

The training images are processed with live wire method based on specified landmarks. The landmarks points are specified through "red star" in each images are shown in below. There are 33 landmarks have been used in each training image for constructing Liver object segmentation. The live wire method can detect the strong edges between the starting points to next point and so on.

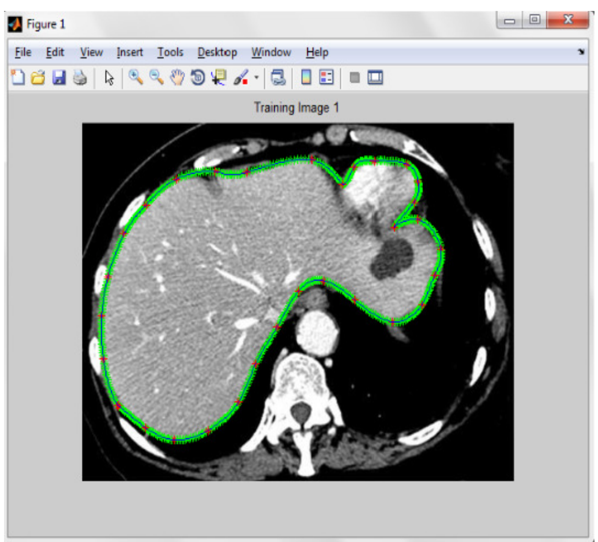

Fig.3. Training Image 1

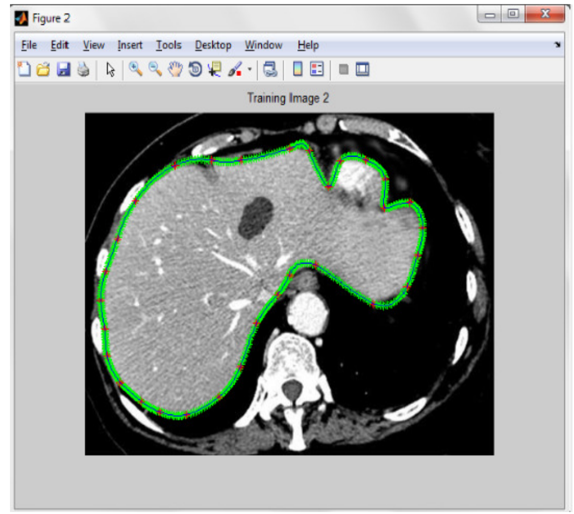

Fig.4. Training Image 2

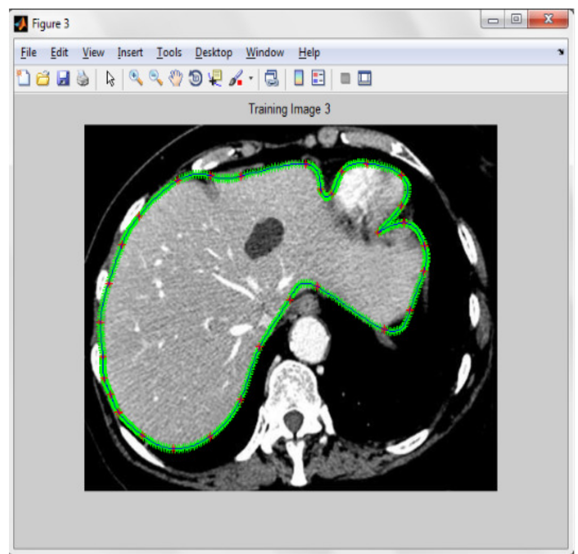

Fig.5. Training Image 3

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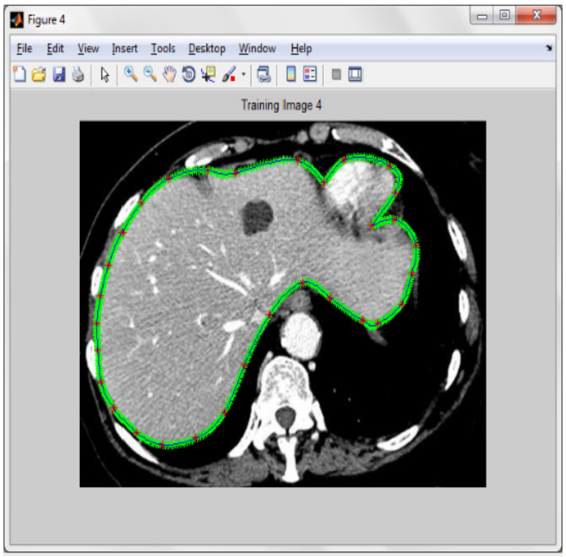

Fig.6. Training Image 4

In this detected edge lines are specified by “Green star” symbols in training images as shown in fig.3. to fig.6. Because here we have to use 5 training images in the same content of liver image.

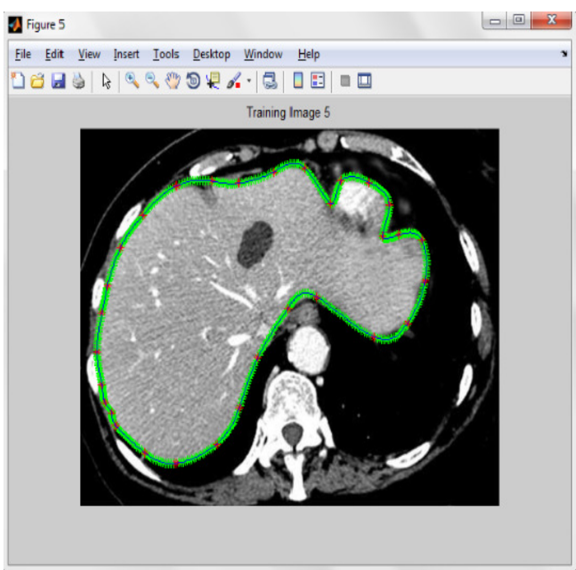

Fig.7. Training Image 5

The training image module having concluded the following information’s are,

- No of Landmark points.
- Landmark values (position information).
- Vertices point information’s (order of Landmarks).
- Detected edges by Live wire based on the specified landmarks.

The training image module has been doing after completion of Training Database module. The outputs of Training Database module are used to function with OAAM. Live wire with AAM method is called OAAM. Here, first we have to apply image database to the shape model of AAM. The shape model functioned and gives a following decision output for constructing OAAM.

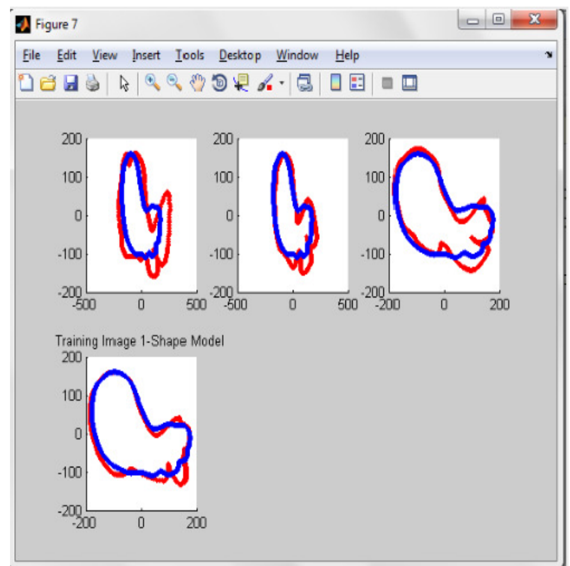

Fig.8.Shape Model of Training Image 1

Fig.8. shows the shape model of the training image 1. It can find the best shape of the specified object of the each training images. Next, the object is applying to the appearances model for constructing texture information by using the parameter of PCA with the output of shape model of the training images.

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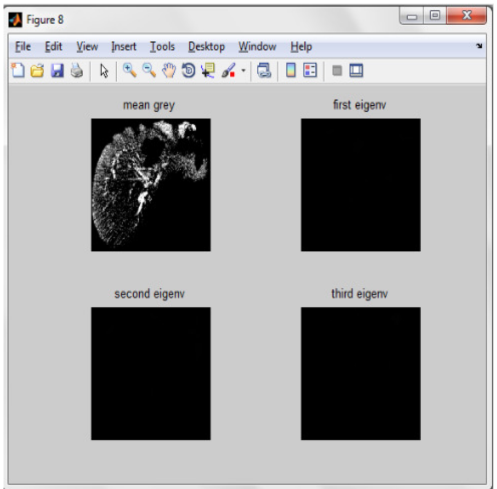

Fig.9. PCA Output

Fig.9. shows the image which is applied for PCA to get the mean shape of the AAM model. The next model is combined model of texture and shape outputs of the images. In this combined model can give a output of RMS difference between the original texture and the combined model.

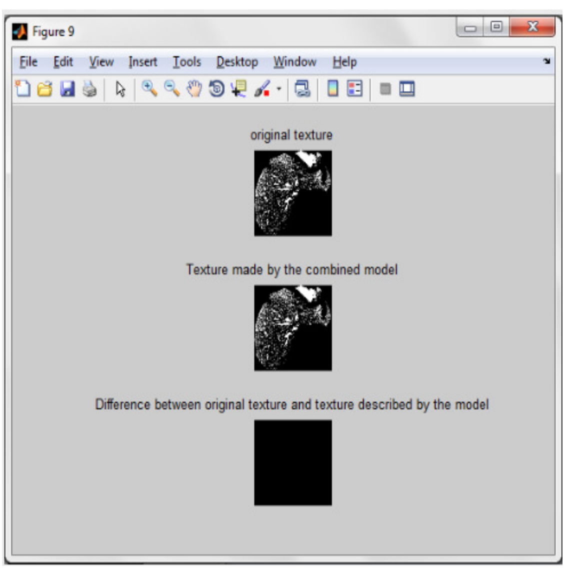

Fig.10. AAM Output

Fig.10. shows the RMs difference between the original texture and the combined model. This is the AAM Output. The last module of this project is testing image is applied and knowing the knowledge of proposed method and efficient of training image Database.

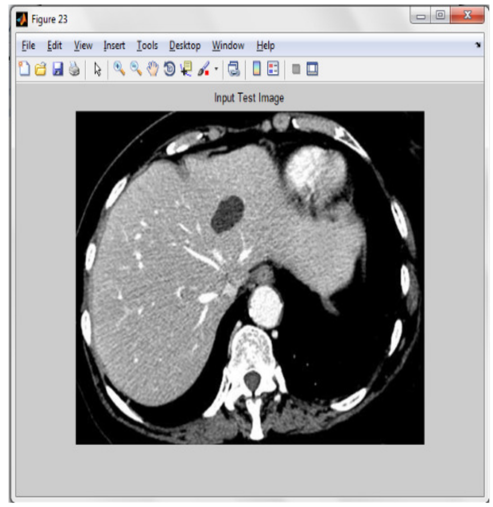

Fig.11. Input test image

Fig.11. shows the input test image. This test image is matching with the trained image. The contour line selection is based on the knowledge of OAAM training output. Because it can select the best edge contour line is selected by initialization step of the algorithm. Here we have the best contour line fixed to the best place of the test image by manually. So in this method is called semi-automatic method.

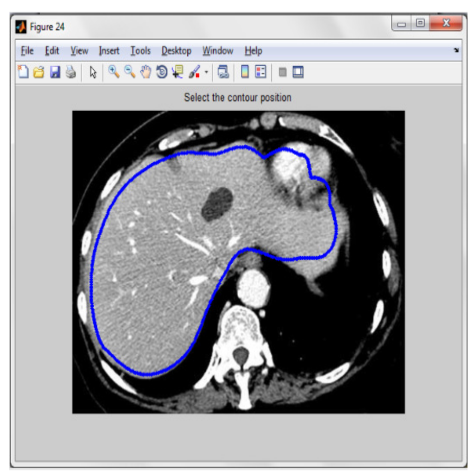

Fig.12. Contour Point Selection

The best contour line is fixed manually to the best place of test image as shown in the fig.12. The next

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following outputs are (Fig.13,Fig.14, Fig.15, Fig.16) shown for detecting suitable boundary line for the corresponding object.

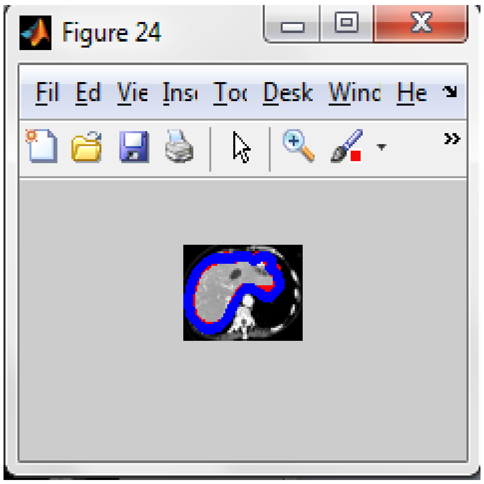

Fig.13. Contour Drawn of the Abdominal Output-Image 1

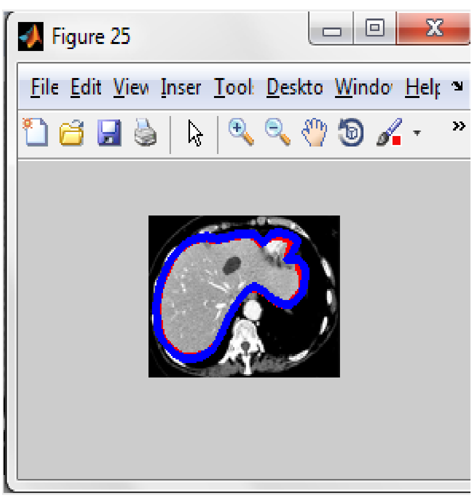

Fig.14. Contour Drawn of the Abdominal Output-Image 2

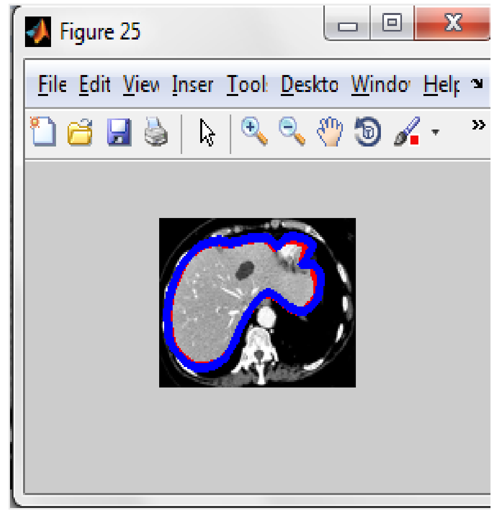

Fig.15. Contour Drawn of the Abdominal Output-Image 3

The above Fig.15. shows the Contour drawn of the abdominal output. This contour point is selected by using automated Live Wire method.

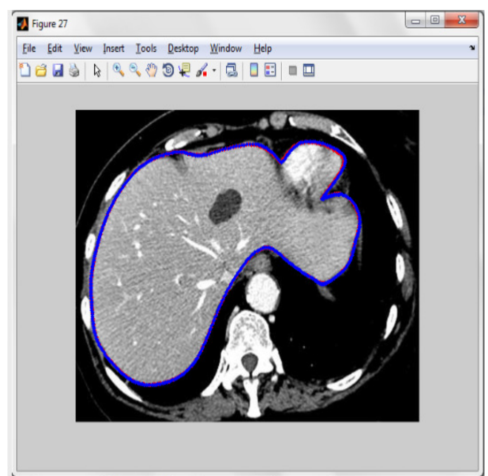

Fig.16. Contour Drawn of the Abdominal Output-Image 4

The final concluded boundary selection of Iterative graph cut with the output of MOAAM as shown in Fig.16.

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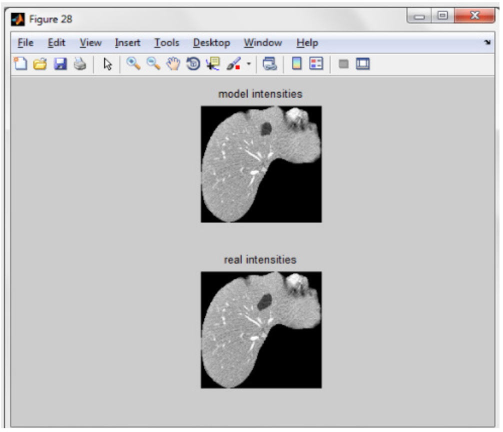

Fig.17. Comparisons of Segmented Liver Image

Fig.17. shows the output of segmented liver image and compared with similar model image from the training set images.

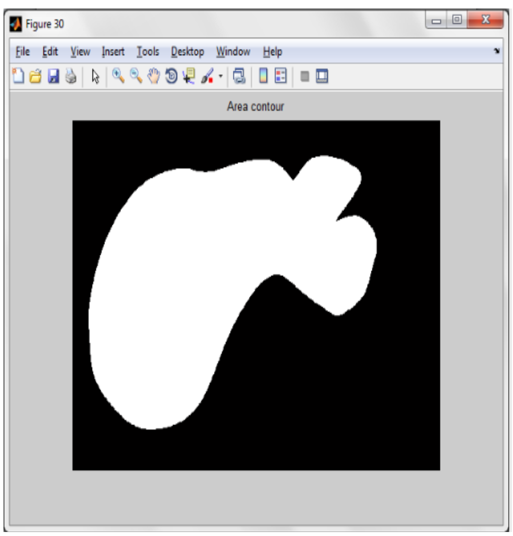

Fig.19. Area Contour

The proposed algorithm of an IGC-OAAM output is as shown in fig.19. The Fig.19. is the representation of foreground and background of the test image for the detected object. It is the binary output for the proposed method as shown in above.

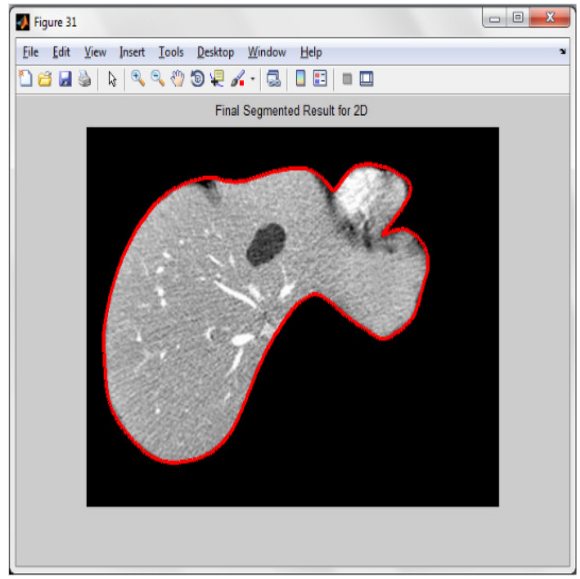

Fig.20. Final 2-D Segmentation

The finalized segmented output, which is the representation of the proposed algorithm for the 2D test image is as shown in figure 4.38. From this output, the proposed method is eligible for 3D image segmentation by mentioning of top and bottom slice for the test 3D image. The training images are shown below. In this section, the training images are processed with live wire method based on specified landmarks. The landmarks points are specified through "red star" in each images are shown in below. There are 33 landmarks have been used in each training image for constructing Liver object segmentation. The live wire method can detect the strong edges between the starting points to next point and so on.

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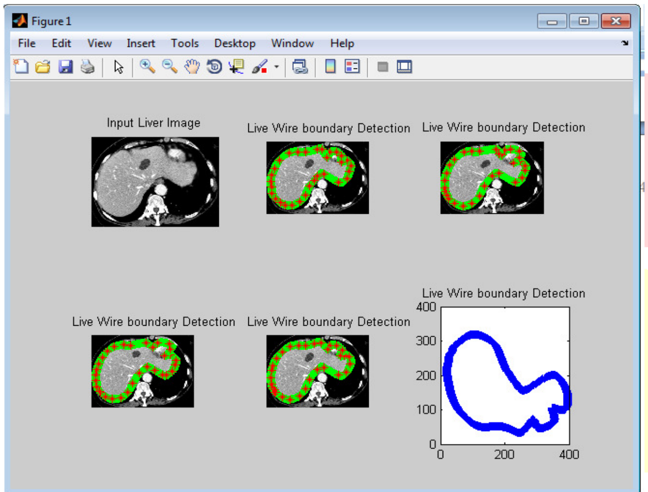

Fig.4.21. Shape Model Detection for given Training Images

The input liver image is given one by one. Here, four training images are given. The strong edge is detected by the live wire method. It can find the best shape of the specified object of the each training images. The final segmentation result is obtained after the process of Active Appearance Model and Iterative Graph Cut and so on. This final 2-D segmentation result is shown below. These results are obtained for every number of input training images given.

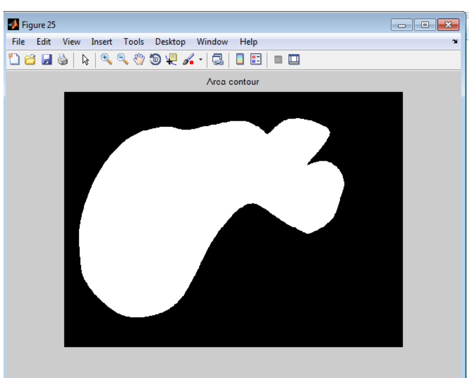

Fig.4.22. Final GC-OAAM Segmentation Output

Here, implementation of multi-shape graph cut is an enhanced work. The proposed method reduces the object delineation time than the existing approach of GC-OAAM. The delineation time is tabulated below. Command window shows the execution time of delineating the object from abdomen.

V.CONCLUSION

Graph Cuts methods represent an established methodology and have been previously applied for liver segmentation purposes; instead, the Geodesic Graph-Cut technique solutions allow avoiding local minima, providing numerical robustness and do not use any shape-prior characteristics that would constrain too strongly recoverable shapes. The Geodesic Graph-cut algorithm produces also better segmentation results than other fully automatic methods found in literature in both terms of accuracy and time processing. This method also effectively combines the Active Appearance Model, Live Wire and Graph Cut ideas to exploit their complementary strengths. It consists of three main parts: model building, initialization, and delineation. For the initialization (recognition) part, employ a pseudo strategy and segment the organs slice by slice via the OAAM method. The purpose of initialization is to provide rough object localization and shape constraints for a latter GC method, which will produce refined delineation.

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