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CLG for Automatic Image Segmentation

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Abstract: **This paper proposes an automatic segmentation method which effectively combines Active Contour Model, Live Wire method and Graph Cut approach (CLG). The aim of Live wire method is to provide control to the user on segmentation process during execution. Active Contour Model provides a statistical model of object shape and appearance to a new image which are built during a training phase. In the graph cut technique, each pixel is represented as a node and the distance between those nodes is represented as edges. In graph theory, a cut is a partition of the nodes that divides the graph into two disjoint subsets. For initialization, a pseudo strategy is employed and the organs are segmented slice by slice through the OACAM (Oriented Active Contour Appearance Model). Initialization provides rough object localization and shape constraints which produce refined delineation. This method is tested with different set of images including CT and MR images (3D image) and produced perfect segmentation results.**

Keywords: **Oriented Active Contour Appearance Model, Active Contour Model, Computed Tomography, Live Wire method, Graph Cut approach.**

I. INTRODUCTION

CIRHOSSIS, lymphoma, pancreatitis, Hodgkin's disease, and renal cell carcinoma, are just a few of the many diseases that can be diagnosed using CT scans of the abdomen. The development of computer-aided diagnosis systems would allow anatomical knowledge coupled with image processing techniques to improve healthcare. Knowledge of anatomy is only of utility if that knowledge is applied to the removal of disease and to the preservation of health. Computer-based systems for the analysis of CT images have many advantages over human interpreters, such as speed, large knowledge base for diagnostic information, and non-sensitivity to fatigue. Organ segmentation is often the first step in computer-aided diagnosis. Segmentation of abdominal organs, such as the liver, kidneys, and spleen, from CT scan imagery has been attracting a fair amount of research recently. Segmentation of abdominal organs presents many challenges. Many artifacts can arise in CT scans, among these are beam-hardening artifacts, which are noticeable as focal areas of low attenuation adjacent to bones; partial-volume artifacts, resulting from spatial averaging of disparate tissues in close proximity and resulting in blurred edges; and streak artifacts, the result of peristalsis, respiratory, cardiac, and patient motion. Also, different organs and tissues have very similar gray levels, which consign thresholding to limited utility.

In [1], the authors devise a graph cut algorithm for interactive segmentation which incorporates shape priors. Interactive or semi-automatic segmentation is a useful alternative to pure automatic segmentation in many applications the graph cuts approach guarantees a global optimum. The related work falls into two categories: segmentation using shape priors, and globally optimal methods for segmentation. The shape priors are embedded into the weights on the edges in the graph, by using a level-set formulation. Transformations of the shape template are also taken into account. The main direction for future research is to examine whether more complex transformations of the template can be easily incorporated into the scheme.

In [2], the proposed algorithm utilizes the shape model of the target organ to gain robustness in the case where the objective organ is surrounded by other organs or tissue with the similar intensity profile. The algorithm labels the image based on the graph-cuts technique and incorporates the shape prior using a technique based on level-sets. The method requires proper registration of the shape template for an accurate segmentation, so propose a unified registration-segmentation framework to solve this problem. In order to reduce the computational cost of the minimization step, the proposed segmentation algorithm operates on homogeneous regions instead of voxels. The algorithm, operating on a properly registered template, captures the boundary of the object, even if it is diffuse or weak. The registration algorithm uses the segmentation energy as a measure of how well the template is fit to the input image, and minimizes that energy over the space of transformations. In this way, the proposed algorithm registers the template and segments the image simultaneously. In [3], In this paper, a probabilistic method for segmenting instances of a particular object category within an image is explained. This approach overcomes the deficiencies of previous segmentation techniques based on traditional grid conditional random fields (CRF), namely that 1) they require the user to provide seed pixels for the foreground and the background and 2) they provide a poor prior for specific shapes due to the small neighbourhood size of grid CRF. Automatically obtain the pose of the object in a given image instead of relying on manual interaction. This "objcut" method include: 1) efficient algorithms for sampling the object category models and 2) the observation that a sampling-based approximation of the expected log-likelihood of the model can be increased by a single graph cut. This method efficiently provides accurate segmentation which resembles the object. The accuracy of the segmentation can be attributed to the novel probabilistic model.

II. MATERIALS AND METHODS

A. Image Segmentation Methods

Image-based methods perform segmentation based only on information available in the image; these include thresholding, region growing, morphological operations, active contours, level sets, live wire (LW), watershed, fuzzy connectedness, and graph cuts (GCs). These methods perform well on high-quality images. However, the results are not as good when the image quality is inferior or boundary information is missing.

Model-based methods employ object population shape and appearance priors such as atlases, statistical active shape models, deformable templates and statistical active appearance models (ACMs). When some object information is missing, such gaps can be filled by drawing upon the prior information present in the model.

Hybrid methods that form a combination of two or more approaches are emerging as powerful segmentation tools. The synergy that exists between these two approaches, i.e., purely image-based and model-based strategies is called as hybrid methods. Hybrid approach can achieve a result much quicker with greater accuracy.

Most of the image-based, model-based and even hybrid segmentation techniques are often tailored for specific body regions (brain, abdomen, etc.) and different image modalities (CT, MRI, etc.). However, it is desirable to generalize image segmentation methodologies for any (or most) body regions and different image modalities and protocols. Furthermore, it is desirable for an image segmentation algorithm not to heavily depend upon the characteristics of fixed shape families and different image modalities. While perhaps some of the above techniques can be generalized in this spirit, few methods have demonstrated to work in this general setting.

B. Active Contour Model

An Active Contour Model (ACM) is a computer vision algorithm for matching a statistical model of object shape and appearance to a new image which are built during a training phase. A set of images, together with coordinates of landmarks that appear in all of the images, is provided to the training supervisor. 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). 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 ACM

C. Live Wire Method

This method (LW) 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 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. In Live Wire method, 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.

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.

D. Graph Cut Approach

Graph cuts (GC) 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 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."Binary" problems (such as denoising a binary image) can be solved exactly using this approach; problems where pixels can be labelled with more than two different labels (such as stereo correspondence, or denoising of a gray scale image) cannot be solved exactly, but solutions produced are usually near the global optimum. 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. In the minimum cut technique the size of the cut is not larger than the size of the any other cut. A cut is maximum if the size of the cut is not smaller than the size of any other cut in the image. 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.

E. Limitations of ACM, LW and GC Approaches

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. The specific shape and appearance information on the object in a given image is difficult to account for in ACM. 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 labelling of the source and sink seeds by a human operator.

III. PROPOSED METHODOLOGY

A. Training Phase

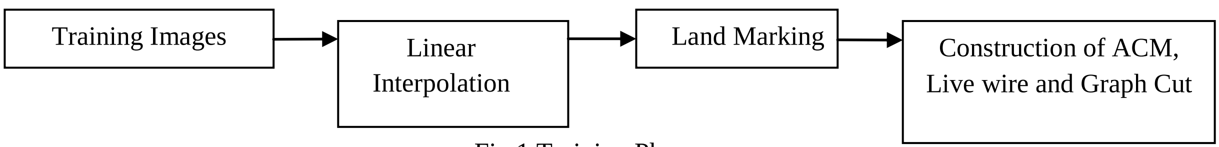

Fig.1.Training Phase

Fig.1. shows the Training Phase model. 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 OACAM 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.

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: Piecewise constant interpolation, Linear interpolation, Polynomial interpolation and Spline interpolation. Linear interpolation is a method of curve fitting using linear polynomials.. 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. Once the landmarks are specified, the standard ACM method is used for constructing the model. The model includes both shape and texture information. Suppose M_j represents the ACM model for slice level and the number of slice levels is , then the complete model M can be represented as $M = (M_1, M_2, M_3, \ldots M_n)$. 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. In our particular case, the cost associated with bel is a linear combination of the costs assigned to its features

$$c(l) = \frac{\sum_{i=1}^{nf} \omega_i c_f(f_i(l))}{\sum_{i=1}^{nf} \omega_i} \qquad (1)$$

where nf is the number of features, is a positive constant, and c_f is the function to convert feature values $(f_i(l))$ at to cost values $c_f(f_i(l))$. In LW, f_i, may represent features such as intensity on the immediate interior of the boundary, intensity on the immediate exterior of the boundary, and gradient magnitude at the center of the bel.

A. Segmentation Phase

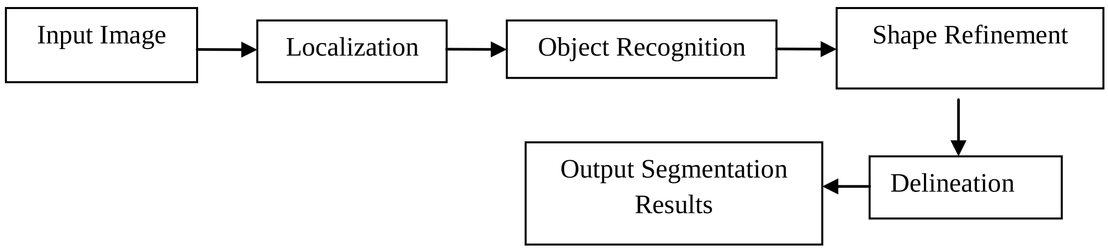

Fig.2.Segmentation Phase

Fig.2. shows the Segmentation Phase model. The aim of slice localization in our approach is to locate the top and bottom slices of the organ. Since the model is already trained for each organ slice, we can use the model for slice localization. The proposed method is based on the similarity of the slice to the OACAM model. For the localization of a top slice in a given image, the top slice model is applied to each slice in the image using the recognition method which is explained

detail in below Section. Then, the slice corresponding to maximal similarity (minimal distance) is taken as the top slice of the organ.

The initialization step plays a key role in our method, which provides the shape constraints to the later GC delineation step and makes it fully automatic. The proposed initialization method includes three main steps. First, a slice localization method is applied to detect the top and bottom slices of the organ. Next a linear interpolation is applied to generate the same number of slices for the given image of a subject, as in the model. Then, the organ is recognized slice by slice via the OACAM method. The proposed object recognition method is based on the ACM. The conventional ACM matching method for object recognition is based on the RMS difference between the appearance model instance and the target image. Such a strategy is better suited for matching appearances than for the detailed segmentation of target images.

The conventional ACM searching method is performed once to obtain a rough placement of the model. Then, the following method is applied to refine the shape model in the ACM. The shape is extracted from the shape model of the ACM, and then the landmarks are updated based on LW using only the shape model and the pose parameters. Subsequently, the refined shape model is transformed back into the ACM. At the same time, ACM refinement is applied to the image yielding its own set of coefficients for shape and pose. The purpose of this step is to finally precisely delineate the shapes recognized in the previous step. An iterative algorithm is proposed by combining GC and OACAM method for the organ's delineation. It effectively integrates the shape information with the globally optimal delineation capability of the GC method.

GC segmentation can be formulated as an energy minimization problem such that, for a set of pixels p and a set of labels, the goal is to find a labelling $f: P \rightarrow L$ that minimizes the energy function $\mathrm{En}(f)$ as follows:

$$\mathrm{En}(f) = \sum_{p \in P} R_p f(p) + \sum_{p \in P, q \in N_p} B_{p,q} \left(f_p, f_q\right) \quad (2)$$

where N_p is the set of pixels in the neighbourhood of $R_p f(p)$ is the cost of assigning label, $f_p \in L$ *to* p *, and* $B_{p,q}$ (f_p, f_q) the cost of assigning labels $f_p, f_q \in L$ *to* p *and* q .

The proposed shape-integrated energy function is defined as follows:

$$\mathrm{En}(f) = \sum_{p \in P}\left(\alpha . D_p \left(f_p\right) + \beta . S_p \left(f_p\right)\right) + \sum_{p \in P, q \in N_p} B_{p,q} \left(f_p, f_q\right) \quad (3)$$

where, α, β, γ and are the weights for the data term, shape term S_p, and the boundary term, respectively. The minimization of the equation (3) can be solved by the GC method.

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.

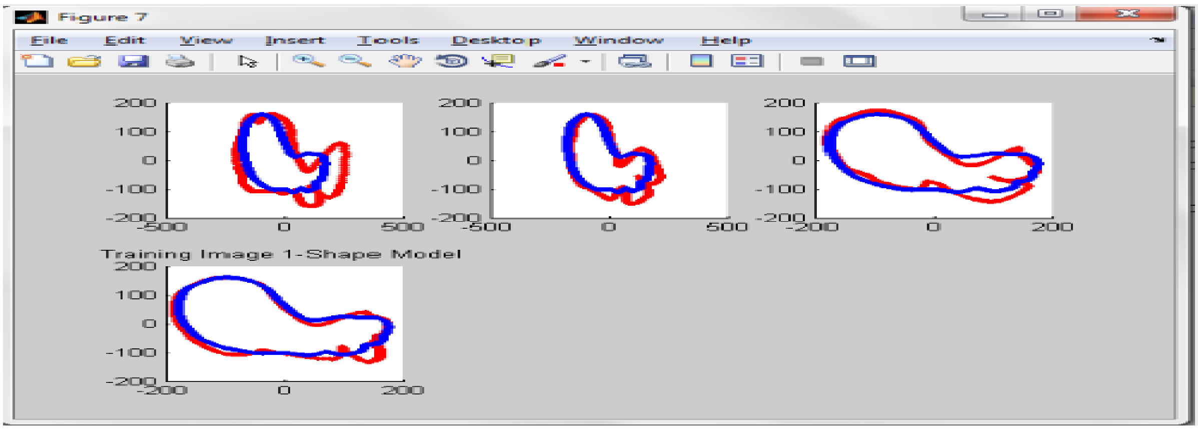

Fig.3.Shape Model of Training Image.

Fig.3. shows the shape model of the training image. 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.

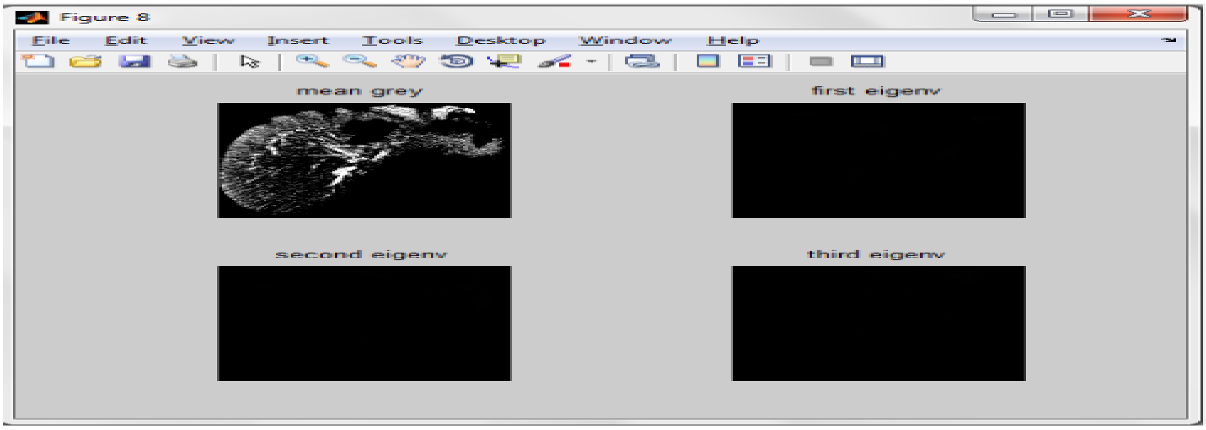

Fig.4.PCA Output

Fig.4. shows the image which is applied for PCA to get the mean shape of the ACM 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.

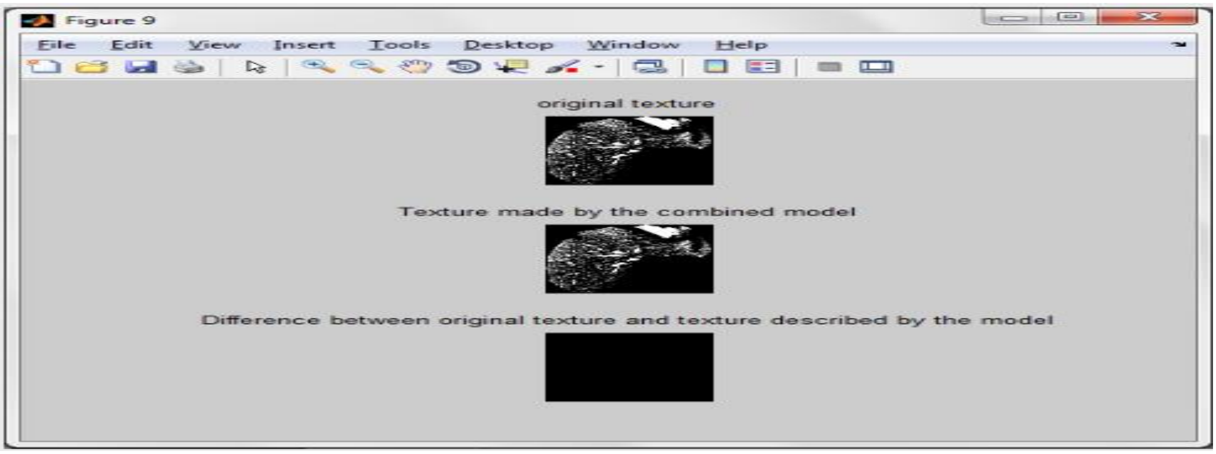

Fig.5. ACM Output

Fig.5. shows the RMs difference between the original texture and the combined model. This is the ACM Output.

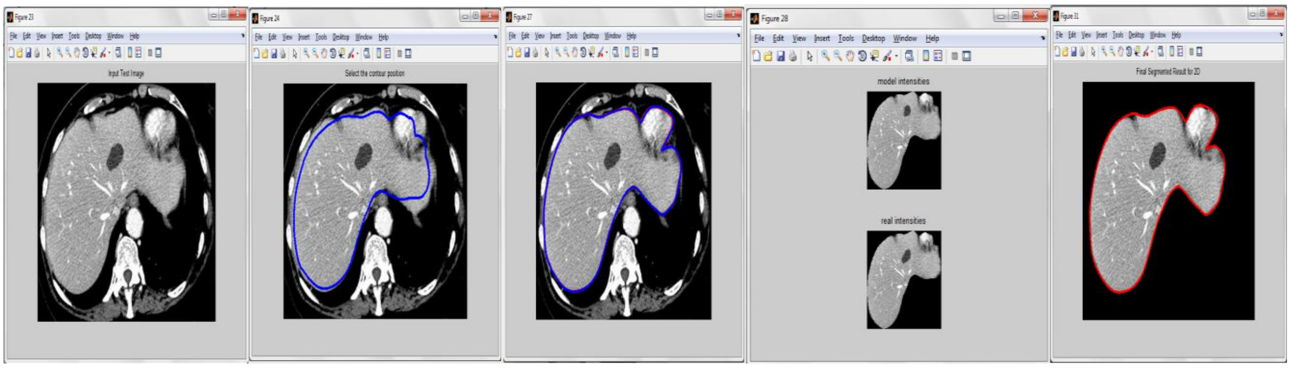

Fig.6. (a)Test Image (b) Selection of Contour Point (c) Contour Drawn of the Abdominal Output (d) Comparisons of Segmented Liver Image With Similar Model Image (e) Final 2-D Segmentation.

The best contour line is fixed manually to the best place of test image. This contour point is selected by using automated Live Wire method. The finalized segmented output, which is the representation of the proposed algorithm for the 2D test image is as shown in Fig.6.

V. CONCLUSION

This paper presented an automatic segmentation method which effectively combines Active Contour Model, Live Wire method and Graph Cut approach (CLG). The aim of Live wire method is to provide control to the user on segmentation process during execution. Active Contour Model provides a statistical model of object shape and appearance to a new image which are built during a training phase. In the graph cut technique, each pixel is represented as a node and the distance between those nodes is represented as edges. In graph theory, a cut is a partition of the nodes that divides the graph into two disjoint subsets. For initialization, a pseudo strategy is employed and the organs are segmented slice by slice through the OACAM (Oriented Active Contour Appearance Model). Initialization provides rough object localization and shape constraints which produce refined delineation. This method is tested with different set of images including CT and MR images especially 3D images and produced perfect segmentation results.

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