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AN ABDOMEN IMAGE SEGMENTATION USING INTEGRATED GRAPH CUT AND ORIENTED ACTIVE APPEARANCE MODEL

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Abstract

A strategic combination of Active appearance model, Live wire and Graph Cut for abdominal segmentation. Medical image segmentation consists of three main parts: model building, object recognition and delineation. In model building, first take an abdomen image as input. The top and bottom slices of organ first manually identified. Linear interpolation is applied to generate the same number of slices then construct the active appearance model and train the LW cost function and GC parameters. In the recognition part combines the active appearance model and live wire method we get oriented active appearance model. The pose of the organs is estimated slice by slice via oriented active appearance model. A further refinement may be needed to adjust the initialization of improperly initialized slices. In the object delineation part, the object shape information generated from the initialization step is integrated into the graph cut cost computation. The method was tested in segmenting the kidneys on a clinical CT data set and also the grand challenge data set. Our aim is to contribute the complementary strengths of these individual methods to arrive at a more powerful hybrid strategy to overcome the weakness of the component methods.

Keywords-- **Active appearance model (AAM), graph cut (GC), live wire (LW), object segmentation, Oriented active appearance model(OAAM), boundary element(bel).**

I. INTRODUCTION

Image segmentation is a fundamental and challenging problem in computer vision and medical image analysis. Several challenges still remain in this area. Efficient, robust and automatic segmentation of anatomy on radiological images is one such challenge. Imaging of human abdomen is one of the challenging application areas of segmentation due to high overlapping intensity ranges of organs. Clinical image segmentation can help clinicians to differentiate and to visualize organs and tissues. To compare the size of tissue orpathologies and to plan surgery and other treatments. Our aim is to combine the complementary strengths of these individual methods to arrive at a more powerful hybrid strategy to overcome the weakness of the component methods.

Image based model based and hybrid methods. Purely image-based methods segmentation based only on information available in the image. It includes, thresholding, region growing morphological operations live wire (LW), and graph cuts (GCs). It performs well on high quality images.

Clinical radiology will increasingly higher emphasis on quantification in practice. The model-based methods employ shape and appearance priors, statistical active shape modes and statistical active appearance models (AAMs).

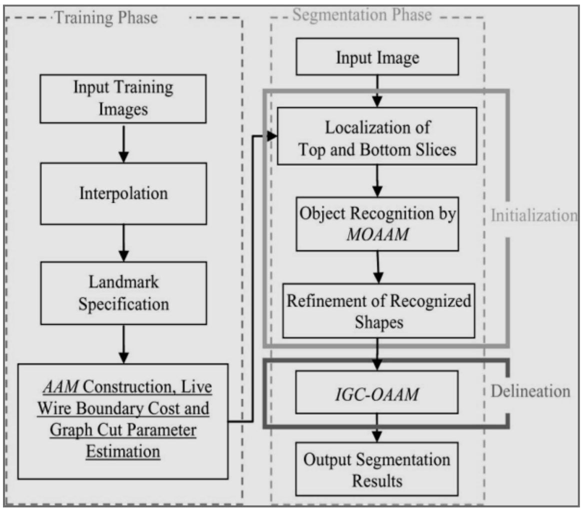

Figure 1. Flowchart of the proposed GC–OAMM system.

Hybrid approaches are attracting a great deal of attention at present. Purely image-based and model-based strategies are used in the segmentation field. We propose a method to segment body organs by effectively combining the Live wire (LW), Active Appearance Model (AAM), and Graph Cut (GC) methods to construct a new technique, called Graph Cut Oriented Active Appearance Model (GC–OAAM). Live Wire is a user-steered 2-D segmentation method the user provides recognition help and the algorithm performs optimal delineation. The main limitation of LW is the anchor points are to be selected on the boundary by a human operator. The Graph Cut Oriented Active Appearance Model Method is the only method that combines the statistical shape and appearance information in the AAM as well as the boundary oriented delineation capability of LW and the globally optimal of the GC method.

II. Problem Description

In many cases, the tissues or organ of interest is difficult to be separated from its surroundings, when they share similar intensity levels. With the other tissues, and their boundaries lack strong edge information. For example, CT technique is weak at imaging soft tissues. It cannot differentiate grey and White matters well in neural tissues.

III. GC–OAMM Approach

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 multiobject Oriented Active Appearance Model (OAAM) method. Next we adjust the initialization of improperly initialized slices. The pseudo 3-D initialization strategy is motivated by two reasons. First, the 3-D initialization is difficult and 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.

The complete methodology of our approach and the object recognition strategies are described.

1.1. Model Building and Parameter Training

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.

1.2. Landmark Specification

Semi automatic or automatic methods are also available for organs because of its simplicity, generality, and efficiency. Manual land marking is still in use in clinical research. In manual land marking, trained operators identify prominent landmarks on each shape. We assessed a semiautomatic land marking method, which is called equal space land marking to show that there is strong correlation between the shapes. Different numbers of land marks 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 we validate manual land marking by the equal-space labeling method.

1.3. AAM Construction

Once the landmarks are specified, the standard AAM method is used for constructing the model. The model includes both shape and texture information. It is combination of Active appearance model and live wire. It represents shape and appearance model.

1.4. LW Cost Function and GC Parameter Training

Similar to the oriented active shape model method an oriented boundary cost function is devised for each organ included in the model. We define the boundary element (bel) as an oriented edge between two pixels with values 1 and 0.

1.5. Recognition/Initialization

The initialization provides the shape constraints to the later GC delineation step and makes it fully automatic. The proposed initialization method includes three main steps.

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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. Then, the organ is recognized slice by slice via the OAAM method. A multiobject strategy is utilized to help with object recognition. One organ is to be segmented; other organs can be included in the model to provide context and constraints. Finally, a refinement method is applied to the initialization result.

1.6. Localization of Top and Bottom Slices

A method to detect invariant slices and single-point landmarks in full-body scans by using a probabilistic boosting tree and Haar features. The aim of slice localization is to locate the top and bottom slices of the organ. Linear interpolation method is used for same number of slices the minimum corresponds to the top slice of the left kidney. For the detection of bottom slice, a similar method is used.

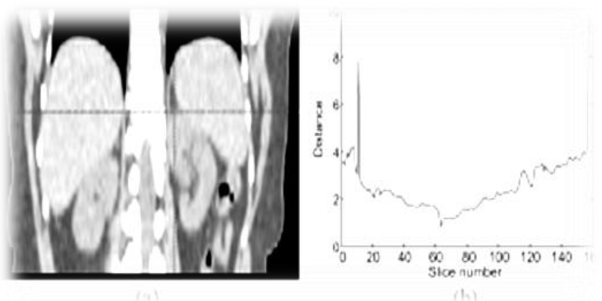

Figure 2. Illustration of top-slice recognition. (a) Coronal view of the abdominal region. Cross point represents the top slice of the right kidney. (b) The distance values of each slice to the top-slice model for the right kidney

1.7. Object Recognition

Object recognition method is based on the AAM. The conventional AAM matching method for object recognition is based on the RMS difference between the appearance model instance and the target image. This is because the AAM is optimized on global appearance, and is thus less sensitive to local structures and boundary information. The LW delineates the boundary it needs good initialization of landmarks and is an interactive method. We integrate the AAM with the LW method to combine their complementary strengths.

The LW is fully integrated with AAM in two aspects: a) LW is used to refine the shape model in AAM and the LW boundary cost is integrated into cost computation during the AAM optimization method. The shape is extracted from the shape model of the AAM, and then the landmarks are updated based on LW using only the shape model and the pose parameters (i.e., translation, rotation, and scale) subsequently, the refined shape model is transformed back into the AAM. At the same time, AAM refinement is applied to the image.

1.8. Delineation

The purpose of this step is to finally delineate the shapes are recognized. We use an iterative algorithm combining GC and OAAM (named IGC–OAMM) method for the organ's delineation. The IGC–OAMM algorithm effectively integrates the shape information with the globally optimal 3-D delineation capability of the GC method.

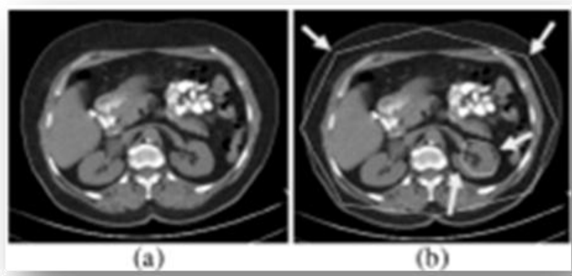

Figure 3. Comparison of conventional AAM and OAAM segmentation. (a) Original image (b) Conventional AAM segmentation

GC segmentation can be formulated as an energy minimization problem such that, for a set of pixels and a set of labels. Recognition is the high-level process of determining roughly the whereabouts of an object of interest and distinguishing it from other objects in the image. Delineation is the low-level process of determining the precise spatial extent of the object in the image. The efficient incorporation of high-level recognition help together with accurate low-level delineation has remained a challenge in image segmentation.

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Table 1.
Number of landmarks and slices used in modeling

Organs	Number of landmarks in organ	Number of landmarks in skin object	Number of interpolated slices
Left Kidney	20	8	32
Right Kidney	20	8	32

It represents the number of landmarks in the right Kidney is calculated and as compare to the number of interpolated slices.

IV. ALGORITHM

With the help of graph cut algorithm we can combine the active appearance model. We give a new method oriented active appearance model. The mean shape and texture models for the objects are landmarked. We have validated manual land marking by equal space labeling method. The accuracy of delineation by IGC-OAAM expressed in TPVF, FPVF and average symmetric surface distance. We describe an evaluation of this method in terms of its accuracy and efficiency. This method is applied for initialization of the organs. Likewise, we can segment multiple objects we can use multiobject oriented active appearance model. Effectively we use Integrated Graph cut appearance method to segment the organ accurately.

1.1. Model building /training phase

- (T1) Specify landmarks on boundaries of objects O1, Om in the training image provided for body region B.
- (T2) Construct a shape model M for the objects in B from the landmarks and training images.
- (T3) Create boundary cost function K.

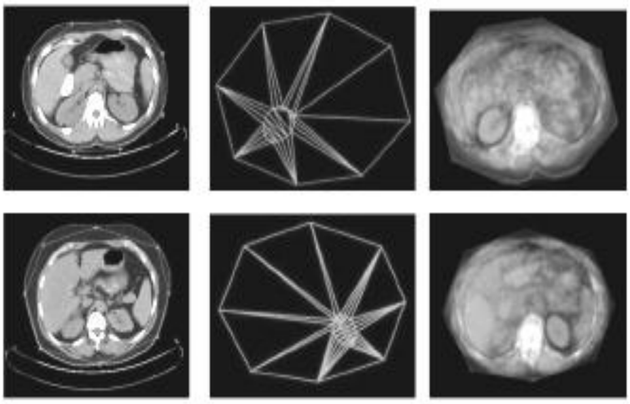

Figure 4. The first, second, third and fourth rows correspond to liver, right kidney, left kidney, and spleen, respectively. (a) Landmarks of th organ and skin on one slice. (b) Corresponding AAM shape model for this slice level. (c) Corresponding AAM appearance model for this slice level.

1.2. Segmentation phase

- (S1) Initialization/recognition: Determine, in the given image I of B of a patient, the pose at which M should be set in I so that the model boundaries are close to the real object boundaries in I. Let the shape instance of the object assembly corresponding to the recognized site be x=(xO1,…,xOm).
- (S2) Delineation: For the shape instances x of the object assembly, determine the best oriented boundaries in I as per the OAAM method.
- (S3) If the convergence criterion is satisfied, output the best oriented boundaries found in S2 and stop. Else subject x to constraints of model M and go to step S2.

The segmentation phase will display the output of the given image. This step is the final step.

V. MODULE DESCRIPTION

1.3. Training phase

In the training phase we landmark the input abdomen image and applying oriented active appearance model to obtain the shape of the organ. Using AAM and Live Wire method to estimate the boundary cost and graph cut parameter are estimated.

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1.4. Segmentation phase

In the segmentation phase we are applying integrated graph cut oriented active appearance model to segment the organ accurately. Using IGC-OAAM methods, segmentation obtained through recognized refined shapes in clinical images (for e.g. Abdomen images)

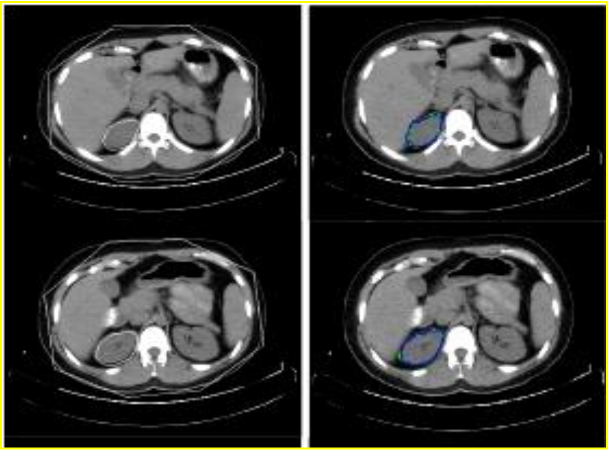

Figure 5. Experimental results for three slice levels of right-kidney segmentation. The left column is the MOAAM initialization result; the right is the IGC–OAMM result

VI. Experimental Results

The proposed methods were tested on a clinical CT data set. This data set contained images pertaining to 20 patients (ten male and ten female, ages 32 to 68), acquired from the precontrast phase of two different types of CT scanners (GE Medical systems). Manually segmented all objects for the purpose of generating ground truth for evaluation.

1.5. Evaluation of the Localization of the Top and Bottom Slices

The proposed slice method was used to detect the top and bottom slices of the right kidney. These organs were manually checked to generate the reference standard of top and bottom positions. We observe that the localization of the top slice of liver is most accurate, which may be due to the high contrast in the image whereas the localization of the bottom of kidney has the largest error, which may be due to the lack of sufficient contrast in that region.

1.6 Evaluation of Initialization

Results of a quantitative evaluation will be implementing. The accuracy in terms of true positive and false positive volume fractions will be shown. TPVF indicates the fraction of the total amount of tissue in the true delineation; the FPVF denotes the amount of tissue falsely identified, which are defined.

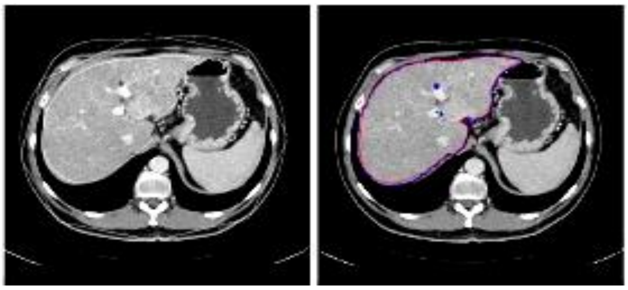

Figure 6. In the MICCAI grand challenge data set the left column is the oriented active appearance model and the right column refers to the integrated graph cut oriented active appearance model.

Table2.
Average Computational Time (In Seconds)

Organ	Average computational time (in seconds)			
	Pseudo-3D MAAM	*3D MAAM*	*Pseudo-3D MOAAM* (initialization)	*IGC-OAAM* (delineation)
Liver	50	732	60	310
Left Kidney	33	495	40	275
Right Kidney	32	476	40	260

The table represents the average value of the computational time of our methods oriented active appearance model and integrated graph cut oriented active appearance model will be implemented and calculated the results as early as possible.

Acknowledgements

We propose automatic anatomy segmentation method. The method effectively combines the Active Appearance Model, Live Wire, and Graph Cut ideas to exploit their complementary strengths. It consists of three major parts: model building, initialization, and delineation. In the recognition part, we take input as abdominal image.

In the image we first landmark the object then applying the combination of active appearance and the live wire resulting oriented active appearance model. It segments the organs slice by slice via the OAAM method. In the delineation part, an iterative GC OAMM method is applied, which integrates the shape information gathered from initialization with a Graph Cut algorithm. The method was tested on a clinical CT data set. The overall segmentation accuracy will be tested using neural network classifier.

The purpose of initialization is to provide a rough object and shape constraints for a GC method, which will produce refined delineation. It is better to have a fast and robust method than a slow and more accurate technique for initialization. This method appears slightly under segment the organs. One of the strengths of our method is to segment the organ during the process of manually delineating the boundaries. The slice localization method aims to localize the top and bottom slices of organs automatically, which is an important part. Manual land marking is still use in clinical research. In a similar manner, it can also be localize any slice by constructing the corresponding slice model. We can apply only one object has been delineated at a time. .With the shape constraints of organs, the IGC–OAMM method can be easily generalized to segment organs simultaneously. For single-object segmentation, global optimality is guaranteed. The method takes about 5 min for segmenting one organ. To make it more practical in clinical applications is one potential solution.

REFERENCES

1. Journal Papers

[1] Freedman and T. Zhang, "Interactive graph cut based segmentation with shape priors," in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recogn., 2005, pp. 755–762.

[2] Ayvaci and D. Freedman, "Joint segmentation-registration of organs using geometric models," in Proc. IEEE Eng. Med. Biol. Soc., 2007, pp.5251–5254.

[3] M. Kumar, P. Torr, and A. Zisserman, "ObjCut," in Proc. IEEEComput. Society Conference on Computer Vision and Pattern Recog-nition, 2005, pp. 18–23.

[4] Malcolm .Y.Rathi, and A. A. Tannenbaum, "Graph cut segmentation with nonlinear shape priors," in Proc. IEEE Int. Conf. Image Process., 2007, vol. IV, pp. 365–368.

[5] N. Vu and B. S. Manjunath, "Shape prior segmentation of multiple objects with graph cuts," in Proc. IEEE Comput. Soc. Conf. Comput.Vis. Pattern Recogn., 2008, pp. 1–8.

2. Text Book

[6] T. McInerney and D. Terzopoulos, Deformable Models, Handbook of Medical Imaging: Processing and Analysis, I. Bankman, Ed. New York: Academic, 2000.

3. Conference Proceedings

[7] Besbes, N. Komodakis, G. Langs, and N. Paragios, "Shape priors and discrete MRFs for knowledge-based segmentation," in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recogn., 2009, pp. 1295–1302.

[8] T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Active shape models—Their training and application," Comput. Vis. Image Underst., vol. 61, no. 1, pp. 38–59, Jan. 1995.

4. Generic Website

[9] "Model-based image segmentation in medical applications" by zhenqian "Active Appearance model" by G.J Edwards, C.J Taylor and T.Cootes "Medical Image Segmentation: Methods and Software" D.J. Withey and Z.J. Koles1, 2