Abdominal Organ Segmentation Using Sparse Representation and Further Combining Graph Cuts an Oriented Active Appearance Models

Das S.S., Bhanuse V.R., Dombale A.B.

Abstract: ***Segmentation of abdominal 3-D organ segmentation (e.g.Liver) from volumetric images forms the basis for surgical planning required for living donor transplantations and tumor resections surgeries. This paper introduces a novel idea of using sparse representations of organ shapes in a learned structured dictionary to produce an accurate preliminary segmentation, which is further evolved based on a strategic combination of the active appearance model ,live wire, and graph cuts for abdominal 3-D organ segmentation. The increased accuracy of the preliminary segmentation translates into faster convergence of the evolution step and highly accurate final segmentations.***

Keywords: Segmentation, sparse representation, AAM, Graph cut.

I. INTRODUCTION

IMAGE segmentation is a fundamental and challenging problem in computer vision and medical image analysis. In spite of several decades of research and many key advances several challenges still remain in this area.

liver segmentation is critical as In abdominal computed tomography (CT) or magnetic resonance (MR) images, there is little difference in the gray-value intensities of adjacent tissues. This leads to loss of boundary for liver in regions close to organs such as: diaphragm, kidney, pancreas, stomach, and heart. Due to these limitations common practice used in clinics is rely either on manual segmentations. This paper presents a radically novel approach to the liver segmentation problem by first producing an initial segmentation from structured sparse representations of liver surfaces, which is further evolved using a regularized 3D level-set formulation to achieve final segmentation.

After preliminary segmentation i.e.structured sparse representation for final segmentation it is desirable to generalize image segmentation methodologies for any (or most) body regions and different image modalities and protocols. so, we propose a general method to segment body organs by effectively combining the AAM and GC methods to construct a new technique.

AAM methods use landmarks.However, 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 can enforce piecewise smoothness. However, they are interactive methods, requiring labeling of the source and sink seeds by a human operator. In this paper, our aim is to combine the complementary strengths of these individual methods to arrive at a more powerful hybrid strategy

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II. LIVER SEGMENTATION USING STRUCTURED SPARSE REPRESENTATIONS

Sparse representation of liver shape in a learned structured dictionary allows for estimating a 3D shape close to the true liver using limited number of samples. it provides a close initialization, thus guarantees a faster convergence

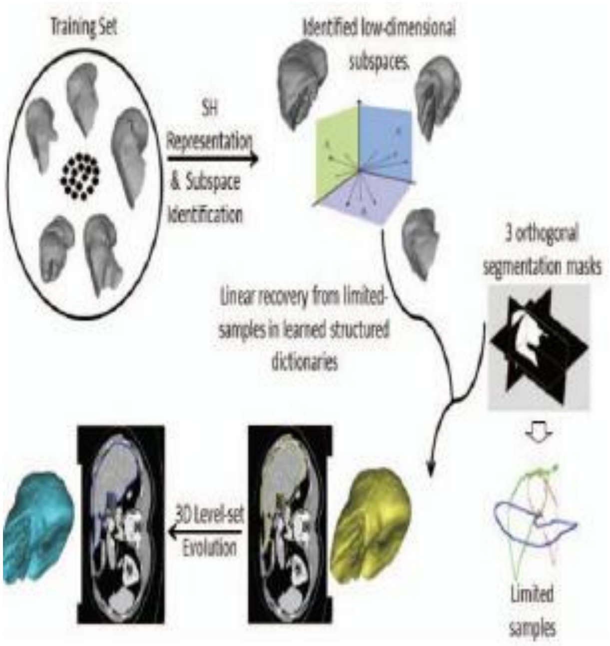

Fig 1: Segmenting liver using Structured Sparse Representations

The segmentation stage consists of two main steps. The first step involves identification of the optimal subspace and reconstructing an estimate of liver shape from limited samples in the identified subspace.

III. GC–OAMM APPROACH

In this at first step AAM is constructed. GC parameters are estimated.

The segmentation phase consists of two main steps: recognition and delineation.

A pseudo-3-D initialization strategy is employed in which the pose of the organs is estimated slice by slice via a multiobject

OAAM (MOAAM) method. The advantages of this new method will be

-The strategy proposed in this paper is a 3-D Technique

-- It does not need registration of shapes

-- It combines rich statistical shape and appearance information in the structured sparse representation & AAM as well as the effective boundary-oriented delineation capability of LW and the globally optimal delineation capability of the GC method.

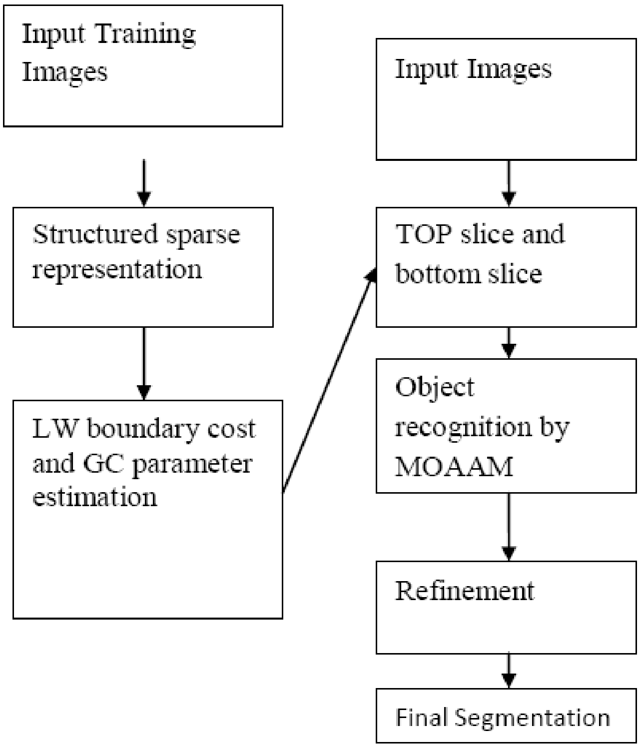

Fig2: Flowchart of the proposed GC–OAMM System

The details of each step are given in the following subsections.

Model Building and Parameter Training

First 2-D OAAM models are constructed for each slice level from the images in the training set and GC parameters are also estimated in this stage.

AAM Construction:-once we get the preliminary shape from the structured sparse representation standard AAM method is used for constructing model.

The model includes both shape and texture information.Suppose Mj represents the AAM model for slice level j and the number of slice levels is n , then the complete model can be represented as M=(M1,M2,…….,Mn).

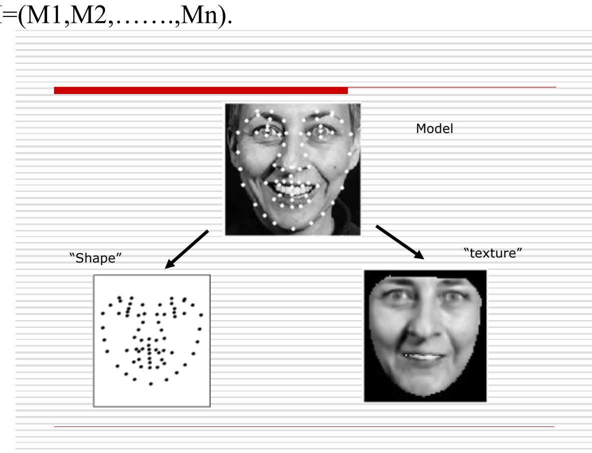

Fig3: AAM Model

Recognition/Initialization

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 OAAM method.

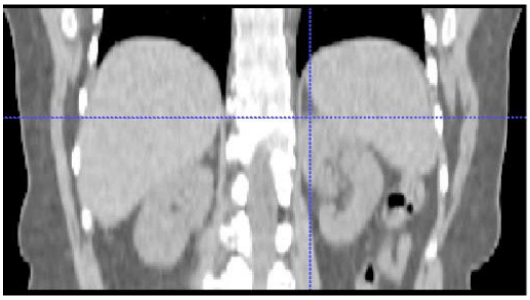

Fig4: Illustration of top-slice recognition. Coronal view of the abdominal region. Cross point represents the top slice of the left kidney

Object Recognition:

AAM method is less sensitive to boundary information and LW delinates the boundary well however,it needs good initialization of landmarks and is an interactive method in this we combine AAM with LW to combine the strengths of both and to obtain a fine segmentation result.

IV. LIVE WIRE

The live-wire segmentation approach formulates the problem of creating the boundary of medical structures as a path-searching problem in a cost weighted graph.

The basic idea is to find the cost optimal paths between a start node and a set of goal nodes. If the edges of the structure are well defined, these paths will align to the structure's outline and form the segmentation result.

In the live-wire method [6], [7], to segment a 2-D boundary, the user initially picks a point on the boundary and all possible minimum-cost paths from this point to all other points in the image are computed via Dijkstra's algorithm [20]. Subsequently, a live wire is displayed in real time from the initial point to any subsequent position taken by the cursor. If the cursor is close to the desired boundary, the live wire snaps on to the boundary. The cursor is then deposited and a new live-wire segment is found next. The entire 2-D boundary is specified via a set of live-wire segments in this fashion.

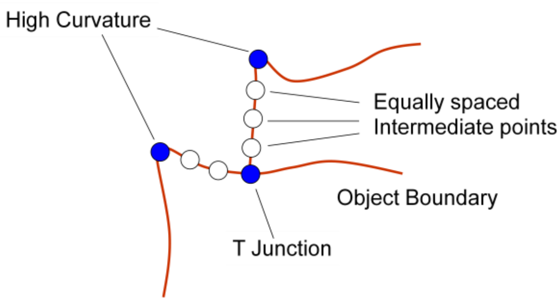

Fig 5:LW Model

V. WHY GRAPH CUTS?

Robust and Efficient Optimization in N-D.

Numerically, image segmentation framework relies on powerful graph cut algorithms from combinatorial optimization

Integrating Topological Constraints

Graph cuts can incorporate some types of topological constraints. For example, the hard constraints can indicate some image pixels a priori known to be a part of the object or background.in this method image is seen as a graph.

The general approach to constructing an undirected graph from an image is shown below.
We take a graph-based approach to segmentation. Let G = (V,E) be an undirected graph with vertices vi € V , the set of elements to be segmented, and edges (vi; vj) € E corresponding to pairs of neighboring vertices. Each edge (vi; vj) €E has a corresponding weight w((vi,vj)),which is a non-negative measure of the dissimilarity between neighboring elements vi and vj . In the case of image segmentation, the elements in V are pixels and the weight of an edge is some measure of the dissimilarity between the two pixels connected by that edge (e.g., the difference in intensity, color, motion, location or some other local attribute).

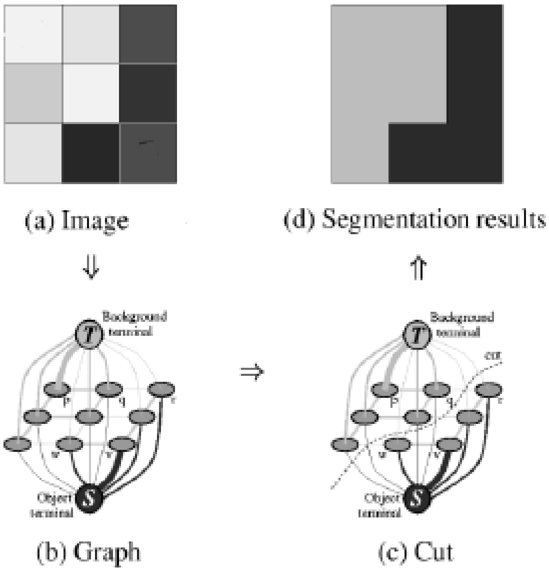

Fig 6: Graph representing a 3-by-3 image and it's segmentation procedure by graph cut method

The idea is as follows: the user marks some pixels as being part of the object of interest,and some as lying outside the object i.e. within the background.
The number of such points is up to the user, but in practice can be quite small (less than ten). Given these constraints,the algorithm tries to find the optimal segmentation such that these hard constraints are satisfied. In particular, a segmentation is scored according to the following criteria:

1. Each pixel inside the object is given a value according to whether its intensity matches the object's appearance model; low values represent better matches.
2. Each pixel in the background is given a value according to whether its intensity matches the appearance model of the background; low values represent better matches.
3. A pair of adjacent pixels, where one is inside the object and the other is outside, is given a value according to whether the two pixels have similar intensities; low values correspond to contrasting intensities (i.e. to an edge).

First step plays a key role in the segmentation process i.e. getting a estimated 3d shape of the organ(e.g.liver).and then the OAMM-GC method is applied for more powerful results.

VI. CONCLUSION

Sparse representations of 3D liver shapes in a learned structured dictionary produces a preliminary segmentation and that result is used for further segmented with a combined method i.e. OAAM-GC, which effectively combines the AAM,LW, and GC ideas to exploit their complementary strengths.so result gives rich statistical shape and appearance information in the AAM and good boundary-capability of LW.

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