SHAPE- AND APPEARANCE-BASED SEGMENTATION OF VOLUMETRIC MEDICAL IMAGES

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ABSTRACT

A novel approach to three-dimensional segmentation, parametric surface representation, and interactive surface modification is reported. The combination of shape-based and appearance-based volumetric segmentation, parametric representation of 3D surfaces, and their interactive modification and editing forms a very powerful paradigm for a variety of volumetric segmentation tasks. Performance assessment of the method for automated segmentation of diaphragm surfaces in volumetric 3D CT images is ongoing.

1. INTRODUCTION

Modern 3-D imaging modalities like CT and MR allow detailed structural and functional analysis of living bodies. In order to do so, large amounts of data must be acquired, analyzed, and interpreted. Availability of highly automated image analysis techniques is the key for taking full advantage of the diagnostic or surgical guidance options that volumetric in-vivo imaging offers.

One of the applications that benefit largely from detailed 3D anatomical information is liver surgery where information about the liver segment defining vascular structure has to be taken into account. Liver segmentation in contrast-enhanced CT images is one of the first processing steps in generating all the data needed for liver surgery planning. In [1], a promising 3D level-set approach to liver segmentation has been presented. Main problems for this and other connectivity-based approaches like region growing occur in the region of the transition between liver and heart. In most cases, the resolution normal to the image plane (z direction) is not high enough to avoid errors caused by partial volume effects.

Segmenting a 3D diaphragm dome which separates the lungs and the heart from abdominal cavity (Figs. 1b,c) is

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likely to overcome this problem. The diaphragm dome typically shows a consistent shape pattern and is therefore well suited for an Active Appearance Model (AAM) based segmentation approach [2]

2. 3-D IMAGE SEGMENTATION OF VOLUMETRIC DATA SETS

2.1. Active Appearance Models

A highly promising, model driven segmentation technique called Active Appearance Model (AAM) was recently introduced by Cootes and Taylor [2]. An AAM describes the image appearance and the shape of an object in a set of examples as a statistical shape-appearance model. AAMs can be applied to image segmentation by minimizing the difference between the model and an image along statistically plausible shape/intensity variations. We have extended the 2D AAM to three dimensions.

2.2. Extension to 3D

One of the main problems in building 3D AAMs is the representation of 3D shapes, due to the need of finding key landmark points on the 3D surface. A manual landmark point placement in 3D is time consuming, error prone, and also presents visualization challenges. Our approach transforms the 3D landmark point placement problem to a 2D one and therefore reduces the amount of necessary user interaction significantly.

2.3. 3D shape representation and landmark point placement

The diaphragm shapes are represented by a 2D closed curve (reference curve) and a gray value image (height image). Both refer to an axial image, which will be denoted as a reference plane. The reference plane is placed in each sample data set on the top of the diaphragm dome. The reference

curve represents the outline of the axial projection of the diaphragm dome (Fig. 1a). The difference in height between dome voxels and the reference plane is stored in the height image. Combined, this 3D shape representation can be viewed as a 2D AAM, except that the gray levels represent shape. Therefore, landmark placement needs only be done for the 2D reference curve.
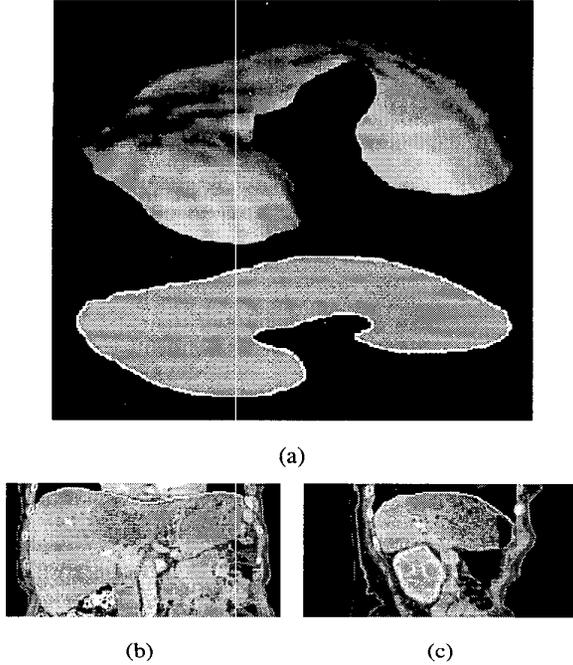

(a)

(b)   (c)

Fig. 1. Diaphragm dome in different views. (a) Axial projection of the 3D dome surface. Coronal (b) and sagittal (c) views showing the top diaphragm dome layer in white.

Using the landmark points x_s of each data set, a statistical model of reference curve shape variations can be generated by means of a Principal Component Analysis (PCA). The linear model

$$x = \bar{x} + P_{s1}b_{s1} \tag{1}$$

can be used to approximate examples of the learned class of reference curves, where $\bar{x}$ denotes the mean reference curve, P_{s1} the reference curve eigenvector matrix and b_{s1} the reference curve parameters. By warping the height images to the mean reference curve shape and sampling them into height vectors, a linear model can be build

$$h = \bar{h} + P_{s2}b_{s2} \quad, \tag{2}$$

where $\bar{h}$ is the mean height vector, P_{s2} the height eigenvector matrix and b_{s2} the height parameters. Thus, the diaphragm dome shape can be represented by the vectors b_{s1}

and b_{s2}. The two parts of the shape model are linked together via the warping function. Note that in this representation same voxel sizes for all data sets are assumed.

2.4. 3D texture representation

Gray values are collected in layers parallel to the diaphragm dome voxel layer. For the matching process it is important to represent additional information about the surrounding non diaphragm voxels. This is done by generating a fringe around the diaphragm dome using a thin plate spline interpolation. Each texture layer is represented by an image. All layers are then warped to the average reference curve. The warped layers are expressed as an intensity vector g by concatenating the intensity vectors from each layer. Then an intensity-normalization to the average intensity of 0 and a variance of 1 is carried out. Applying PCA to the normalized data a linear model

$$g = \bar{g} + P_g b_g \tag{3}$$

for the intensity vector g can be obtained, where $\bar{g}$ denotes the mean intensity, P_g the intensity eigenvector matrix and b_g the intensity parameters.

2.5. Building a 3D AAM

The two shape coefficient vectors (b_{s1}, b_{s2}) and the gray-level intensity coefficient vector (b_g) are concatenated in the following manner

$$b = \begin{pmatrix} W_s \begin{pmatrix} b_{s1} \\ W_h b_{s2} \end{pmatrix} \\ b_g \end{pmatrix} = \begin{pmatrix} W_s \begin{pmatrix} P_{s1}^T(x-\bar{x}) \\ W_h P_{s2}^T(h-\bar{h}) \end{pmatrix} \\ P_g^T(g - \bar{g}) \end{pmatrix} \quad, \tag{4}$$

where W_s and W_h are diagonal matrices relating to different units of shape and intensity and a different voxel size in z direction compared to the equal size in x and y directions. A PCA is applied to the sample set of all b vectors, yielding the model

$$b = Qc \quad, \tag{5}$$

where Q is a matrix consisting of eigenvectors and c are the resulting appearance model coefficients.

Applying this procedure to a set of 3D training objects results in an 'average object' and its characteristic variations in 3D shape and intensity. A new diaphragm dome shape can be generated as follows:

1. Generate a new reference curve shape x and height vector h.
2. Calculate a new diaphragm dome shape by converting h into an image and warp it according to the reference curve.

3. Generate a new intensity vector g and split it up into the layer intensity vectors.

4. Convert the layer intensity vectors into images, warp them according to the reference curve shape and translate the gray values in height according to the height image and layer number.

2.6. Matching the 3D AAM to volumetric images

The 3D AAM can be used for segmentation of volumetric image data sets by minimizing the difference between the model appearance and a target volume data set by deforming the appearance model along the characteristic model eigenvariations using a gradient descent minimization. This involves finding affine transformation parameters t, global intensity parameters u, and appearance parameters c that minimize $|\delta g| = |g_{target} - g_{model}|$, where g_{model} denotes the appearance model intensity vector and g_{target} the intensity vector at the current model position in the volume data set. g_{target} is generated in an inverse procedure by reversing steps 4 and 3 of the dome generation process outlined in section 2.5. The model intensity vector g_{model} is derived from the appearance coefficients c and is later modified by the global intensity parameters u.

For an effective update of the parameters c, t and u a relation between these parameters and δg has to be found. This can be done by multivariate regression as described in [2].

After placing the reference plane at the top of the diaphragm dome and roughly moving the 3D AAM in x and y directions to a good starting position, a conventional 2D AAM matching procedure is used [3]. However, a key difference between the 3D AAM and the 2D AAM is that the error criterion $|\delta g|$ is calculated for the 3D volume data.

3. MODELING OF 3D REGIONS WITH PARAMETRIC SURFACES

Modeling of a 3D region with a parametric surface enables high-quality rendering as well as effective editing of the region. To represent a 3D region with a parametric surface, it is required to parameterize voxels defining the region. We parameterize a 3D region by approximating it with a polygon mesh. A subdivision mechanism is developed that starts by approximating a 3D region with an octahedron. Then the triangular faces are subdivided to smaller ones until the maximum distance between the triangular mesh and the 3D region reaches a required tolerance.

To represent a 3D region with a parametric surface, the vertices of the polygon mesh are considered the control points of a rational Gaussian surface [4]. The parameters at the control points are estimated by subdividing a sphere

in parallel to the region subdivision and assigning the parameters at the mesh vertices obtained from the sphere subdivision to the corresponding mesh vertices obtained in the region subdivision. Representation of a 3D region by a rational Gaussian surface enables editing of the region by interactively moving its control points.

4. REFINEMENT OF A SEGMENTATION RESULT VIA EDITING OF A PARAMETRIC MODEL

Medical image segmentation methods often produce 3D regions. Due to many unknown parameters of images and depending on the input image provided, automated methods may produce results that contain errors. In medical image analysis errors cannot be afforded. Therefore, the results are examined and revised as needed. It is desirable that such revisions be quick and easy.

The parametric model of a 3D region as outlined in the preceding section enables effective editing of a segmentation result. Once a 3D region is represented by a parametric surface, by overlaying the surface with the volumetric image, a user can examine the correctness of the result by viewing the cross-sections of the images. If an error is observed, the user can edit the surface just like editing a geometric model while observing both the volumetric image and the surface. The user may stop the editing process when a desired result is achieved.

After editing, the obtained surface can be discretized to replace the original segmentation result. A parametric model not only enables effective editing of a 3D region, it also enables rendering of the region in high quality for navigation and visualization purposes.

5. SHAPE AND APPEARANCE SEGMENTATION AND VIRTUAL LIVER SURGERY PLANNING

Surgical resection is the treatment of choice for malignant liver tumors. An accurate 3D representation of the patient's liver together with outlined liver segments, liver tumors and vascular structures is able to provide the surgeon with the necessary information to decide whether a resection is possible or not and how to carry out the surgical approach. Liver and liver tumor segmentation is a non trivial task, due to their shape variation, inhomogeneous appearance, partial volume effects and low contrast to adjacent tissue. For a manual segmentation of the liver in volumetric CT images, up to three hours are needed, depending on the number of image slices.

The developed method will consist of the following main steps:
1. Segmentation of thoracic cavity and diaphragm
2. Liver segmentation
3. Tumor segmentation

4. Interactive 3D editing

5. Visualization and surgical planning

As mentioned earlier, diaphragm segmentation is one of the first steps toward automating this process. First, a diaphragm-specific 3D-AAM will be used to separate the heart from the liver. This step addresses the partial volume effect between heart and liver that can be observed in most cases. Then, the abdominal cavity side walls will be segmented with another 3D-AAM. We expect that liver and liver-tumor segmentation will be performed in a single step and will utilize gray-level based approaches. Throughout the process, parametric surface representation will be used for interactive modification as needed.

6. RESULTS

Currently, 18 volumetric CT datasets depicting lower thoracic cavity are available. An interactive tool for AAM training has been developed that allows highly accurate specification of the diaphragm surface location by simultaneous visualization of image data in three views – coronal, sagittal, and axial. Using this training tool, a 3D AAM was built representing average diaphragm shape and appearance as well as most significant modes of shape and appearance variation. The AAM-defined model can be interactively modified to match the previously unseen image data as described in Section 4 and demonstrated in Fig. 2. Work on perfecting the matching process allowing automated segmentation of the diaphragms in volumetric 3D CT data sets is under investigation.
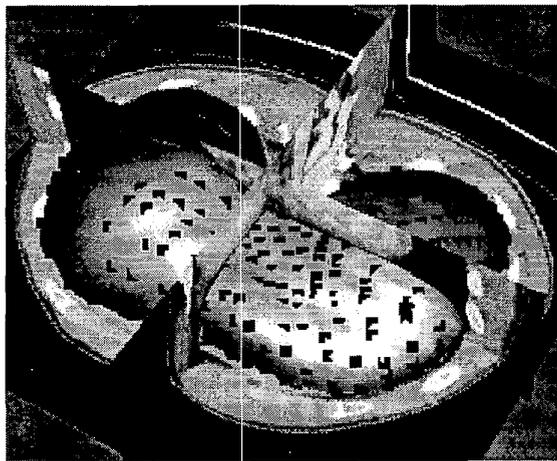

Fig. 2. Interactive modification of a diaphragm dome surface can be achieved by moving the marked control points. Diaphragm surface is interactively fitted to the 3D CT data set.

7. DISCUSSION

Volumetric medical images are frequently non-isotropic. Resolution in z direction is typically lowest and may not be sufficient to capture the whole diaphragm dome in some cases. Therefore we define the diaphragm dome segmentation problem as finding the top layer of the diaphragm dome.

Generating a sufficing number of training samples to build the AAM can be very time consuming. The interactive reviewing tool described above can be used to jumpstart the training model generation. First, several examples are segmented manually. Then, a 'first-attempt' 3D AAM is built, which will likely have limitations in its modeling/segmentation capabilities. Nevertheless, the output is a good starting point for an interactive reviewing step carried out by experts. In this time-inexpensive manner, the learning set can be easily expanded. Once the training base is sufficiently large, the interactive reviewing tool will be used for a correction of occasionally appearing local segmentation errors.

8. CONCLUSION

The combination of shape-based and gray-level-based volumetric segmentation, parametric representation of 3D surfaces, and their interactive modification and editing forms a very powerful paradigm for a variety of volumetric segmentation tasks.

A general medical image segmentation approach was reported that has a potential to be used in a complex problem of segmenting liver and liver tumors from volumetric whole-body-CT images. While substantial work needs to be done before our method reaches clinical routine, the achieved progress warrants additional development of the presented paradigm.

9. REFERENCES

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