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AN IMPROVED GROWING DEFORMABLE SURFACE PATCHES MODEL FOR ANALYSIS OF MEDICAL IMAGES

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ABSTRACT

An improved growing deformable surface patches algorithm and its application in medical image analysis are presented in this work. In this proposed method, a growing mechanism is introduced to 3D deformable model. After a surface patch is initialized within the external force field, it is deformed to reach and stop at the boundary of the object and anchored there. New surface patches are initialized based on the existing anchored patch for deformation in the subsequent deformation iterations. This process is repeated until a closed out surface of the object is obtained. With the growing framework, the proposed deformable model could achieve topology adaptive surface extraction by connecting new surface patches with active patches and automated triangulating the square patch in particular situations. Further more, surface curvature adaptiveness is achieved in the proposed deformable model by associating the surface curvature with the size of the surface patches.

Keywords: 3D surface extraction, adaptive topology, deformable model, medical image analysis

1. INTRODUCTION AND RELATED WORK

Deformable models are used intensively in object detection. There has been a significant research effort for achieving 3D object detection based on deformable models as acquisition of 3D data, particularly in biomedicine, has become more and more common for the past decade. However topological transformation is a problem for 3D deformable surface models. In those deformable models which incorporate a priori geometric knowledge, the object of interest is assumed to have the same topology with the object in training samples where the priori knowledge comes from. Even in many deformable models without incorporating a priori geometric knowledge, topology of the object must be known in advance since classical deformable models are parametric and are incapable of topological transformations without additional machinery.

Deformable models have mainly two formulations: parametric form and implicit form. The advantage of implicit deformable models is their topological adaptability of the model. However, their topology is not explicit. If there are gaps in the object, the evolving model will leak through gaps. Deformable models in parametric form are not only compact, but also is robust to both image noise and boundary gaps. However traditional parametric deformable models can not handle topological transformation.

In the past years, many ideas were introduced in traditional 2D or 3D deformable models in order to increase their performance. 2D and 3D statistical deformable models have been a widely used method in computer vision. A priori knowledge is incorporated into deformable models for robust automatic object segmentation and reconstruction. However, it also has problems in real applications. The complicated procedure for building a PDM (Point Distribution Model) from training data is difficult and time consuming, especially for its applications in 3D object detection in medical image analysis. The tradeoff of statistical deformable models is to lose their flexibility. If the target is not similar to any sample in the training set, the result will be bad because the strong parameter constrains will limit the template to find the correct boundary of the object. This situation does happen in real application. For example, the size, shape, location and rotation of brain tumor is greatly variable according to different patients. It is very hard to train a PDM in this case. And the shape of brain ventricle, which is widely used to test statistical deformable in recent published papers, will also vary significantly and unpredictably because of diseases. Statistical deformable models will meet great difficulty to detect objects with arbitrary shape variance. In this aspect, traditional explicit deformable models have more flexible ability. However, traditional explicit deformable models are incapable of topological transformation without additional machinery. Parametric deformable model are bound to their intrinsic topology: deformable models give prior information on the shape of the objects to recover. If the original model shape is too different from the data, the model might not be able to deform correctly.

A dynamic model, topologically adaptable surfaces (T-surfaces), introduced by McInerner [1] can automatically change its topology with regard to its variable geometry. T-surfaces use a superposed affine cell grid to reparameterize the models during their evolution. As the T-surface move under the influence of external and internal forces, it is reparameterized with a new set of nods and triangles by computing the intersection points of the model with the superposed grid. This reparametrization performs topological transformations in an implicit way.

An explicit deformable model: deformable meshes with automated topology changes was presented by Lachaud [2]. In this model, a framework for topology changes is proposed to extract complex object: within this framework, the model dynamically adapts its topology to the geometry of its vertices according to simple distance constrains. Therefore no a priori assumption is made on the topology of objects. The topology of the model is adapted to the geometry of its vertices at each step without user interaction, topological modifications are made locally.

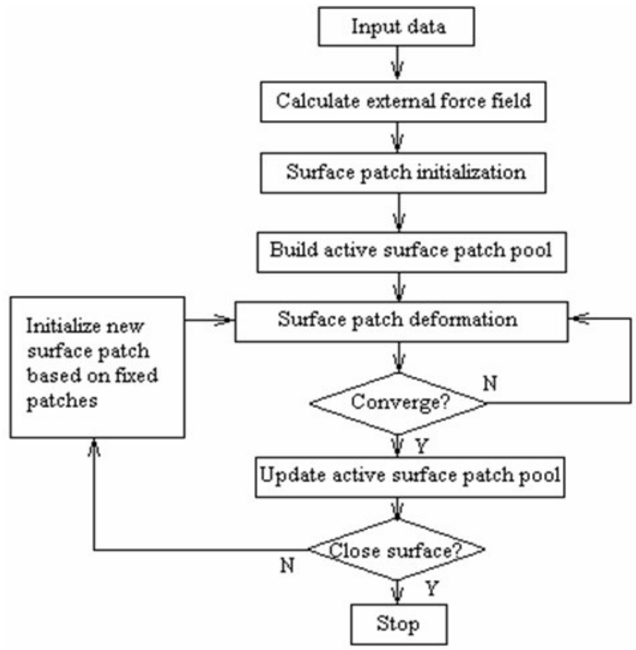


Fig. 1. Flowchart of growing deformable surface patches model

2. OUR APPROACH

2.1. Framework

The proposed algorithm includes two iteration loops (shown in Figure 1): the inner loop for deforming each surface patch and outer loop for the growth of the entire surface model. The inner loop is to deform surface patches separately with the help of particular internal force which is designed to support deformation with "anchored" edge. More details are presented in Section 4. The outer loop, based on the growth mechanism, is designed to achieve topologically adaptable object detection.

In our model $\mathbf{M}, \mathbf{M} \in \mathbb{R}^3$, the smallest element is a square surface patch $\mathbf{S}_i$ [3]. Only a surface patch $\mathbf{S}_1$ is initialized in the first stage. Under the influence of internal force f_{int} and external force f_{ext}, it is deformed to reach and stop at the boundary of the object and is labelled as an "anchored" patch $\mathbf{S}_{anc,1}$. Then a new surface patch, $\mathbf{S}_i, i \neq 1$, is initialized based on the existing anchored patch $\mathbf{S}_{anc}$ for deformation in the next iteration.

Two connected patches, $\mathbf{S}_i, \mathbf{S}_j, i \neq j$, will share a common edge. This edge will be set as "connected" edge. The bare edge which is free and ready for connecting with other patch is labelled as "bare" edge. New surface patches $\mathbf{S}_i$ are generated from "anchored" patches $\mathbf{S}_{anc}$ and the participant edges are relabelled. In order to represent the entire out surface of an object without overlapping or gap, a square patch is triangulated by merging two vertexes when the average curvature of the surface increases or decreases significantly or in the situation that surface patches come to a pole of the object to generate a close out surface when the average curvature of the surface does not change.

This process is repeated until a closed out surface of the object is obtained. The stopping criteria of each surface patch is similar with traditional deformable models: if the total energy on surface patch reaches the minimum value, the deformation procedure for this surface patch stops. Our model will stop if the entire closed surface stopping criteria is satisfied: there is no "bare" edge among all the surface patches $\mathbf{S}_i$ any more. The final result of our model, $\mathbf{M}$, is a closed surface which consists of a number of surface patches $\mathbf{S}_i$ (square patches or triangulated patches). Each surface patch is connected with nearby patches, sharing the same edges of the connected patches.

2.2. Internal Forces

We define three internal forces that depend on the surface patch itself and the mean size of the surface patch which is a global parameter:

$$f_{int}(U) = f_c(U) + f_e(U) + f_a(U). \tag{1}$$

If $U(x, y, z)$ is a knot of the new surface patch, $\mathbf{u}$ expresses its coordinates, $\bar{\mathbf{u}}$ is the mid-point of the nearby

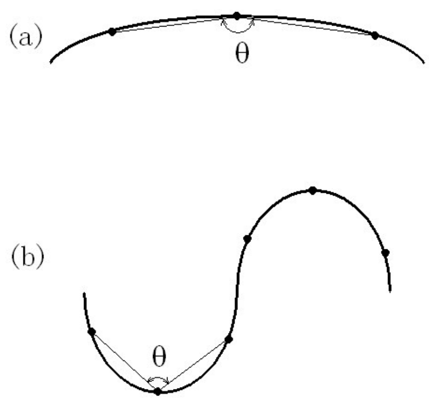


Fig. 2. (a) θ is near 180^o if the surface of the object is simple; (b) θ decreases when the surface of the object is complicated

knots of U in the new surface patch.

(A) f_c is a force of curvature regularization which smoothes the shape of the surface patch, where α_c is the rigidity coefficient.

$$\forall U \in \mathbf{S}_i, f_c(U) = \alpha_c(\bar{\mathbf{u}} - \mathbf{u}) \tag{2}$$

(B) f_e is a force that spreads localized deformations and makes the surface patch adaptive to the local curvature. It regularizes the edge lengths along the whole surface and expresses the binding energy. The local curvature of the model will also influence f_e. θ, the angel between two edges of adjacent knots, is near its maximum 180^o if the surface of the object is simple, shown in Figure 2 (a). When the surface of the object is complicated, its radius of curvature decreases significantly, θ will decrease as well.

Different objects, even different portions in the same object, have different levels of complexity. To make our method adaptive to the complexity of the object, we adjust the size of the individual surface patch with respect to the local curvature by adjusting the width of surface patch. Thus, f_e is defined as:

$$\forall U \in \mathbf{S}_i, f_e(U) = \alpha_e \sum_{V \in \mathbf{S}_i, V \neq U} \frac{\mathbf{v} - \mathbf{u}}{\parallel \mathbf{v} - \mathbf{u} \parallel}(\parallel \mathbf{v} - \mathbf{u} \parallel - \frac{d_a}{3}), \tag{3}$$

where

$$d_a = \frac{1}{2} d_w (1 - cos\theta), \tag{4}$$

α_e is the stiffness coefficient, d_w is the desired mean edge length of surface patches, V is a knot in $\mathbf{S}_i$.

(C) f_a is a force to support deformation with "anchored" edges, where α_a is the response coefficient.

$$\forall U \in \mathbf{S}_{ia}, f_a(U) = -f_c(U) - f_e(U), \tag{5}$$

$$\forall U \in \mathbf{S}_{if}, f_a(U) = \alpha_a \sum_{V \in \mathbf{S}_{ia}} \frac{f_a(V)}{\parallel \mathbf{v} - \mathbf{u} \parallel},$$

2.3. External Forces

The function of external force field, $\mathbf{E_{ext}}$, in 3D growing deformable surface patches algorithm is to guide our surface model to move towards the boundaries of the target object. We put the new generated surface patch $\mathbf{S}_i$ in the force field $\mathbf{v}$ first. Every point $U, U \in \mathbf{S}_i$ is influenced by the force field. The external force on point U is:

$$\forall U \in \mathbf{S}_i, f_{ext}(U) = \mathbf{E_{ext}}(U) \tag{6}$$

Here we choose gradient vector flow (GVF)[4] field as our external force field which has a large capture range and is able to move surface model into boundary concavities. As mentioned in [4], GVF can be generalized to higher dimensions for application.

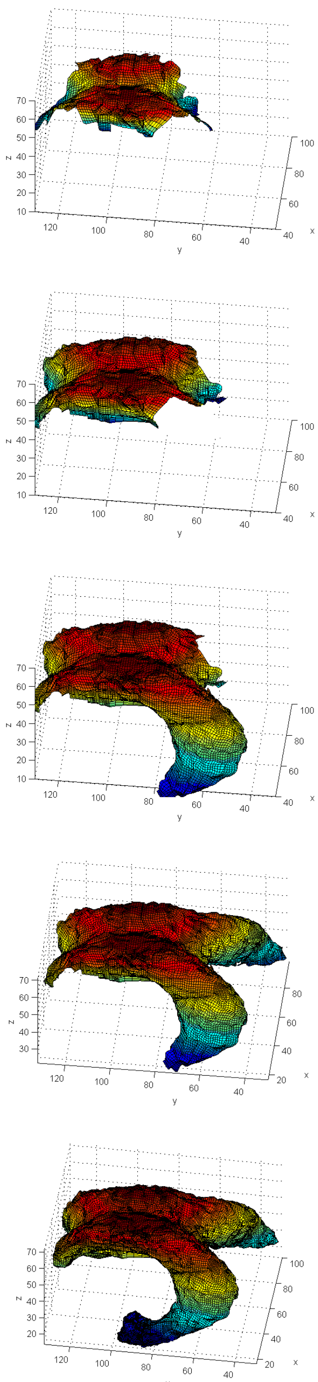
3. EXPERIMENTAL RESULTS AND CONCLUSION

Our growing deformable surface patches method could be applied in medical image analysis. The external forces field of the object surface is calculated using 3D modified GVF. In this experiment, we segment and reconstruct the ventricle from a T2 weighted MR image of human brain. The volume image size is $256 \times 256 \times 138$. The model parameters are: $d_w = 6$, $\alpha_c = 0.175$, $\alpha_e = 0.175$, $\alpha_a = 0.5$, $\alpha_1 = 0.1$ and $\alpha_2 = 0.9$. The surface evolution result of the ventricle detection is shown in Figure 3. The final result of the ventricle detection is shown in Figure 4. To evaluate our algorithm, we measure the minimum distances between 100 manually marked boundary points and our obtained surface(Table 1).

Table 1. Experimental results of brain ventricle detection

Number of Surface Patches	794
Initial Patch Width	6 voxel
Number of Marks (manual)	100
Average Distance Error	0.41 Voxel
Maximum Distance Error	3 Voxel

With the novel growing framework, the proposed deformable model could achieve topology adaptive surface extraction by connecting new surface patches with active patches and automated triangulating the square patch in particular situations. Compared with existing topological adaptive explicit deformable models, 1) we reduce the computational costs by considering the "active" patches only in



(a)

(b)

(c)

(d)

(e)

Fig. 3. The growing steps of our deformable model in human brain ventricle detection: (a) result with 100 Surface Patches; (b) result with 200 Surface Patches; (c) result with 300 Surface Patches; (d) result with 400 Surface Patches;(e) result with 600 Surface Patches.

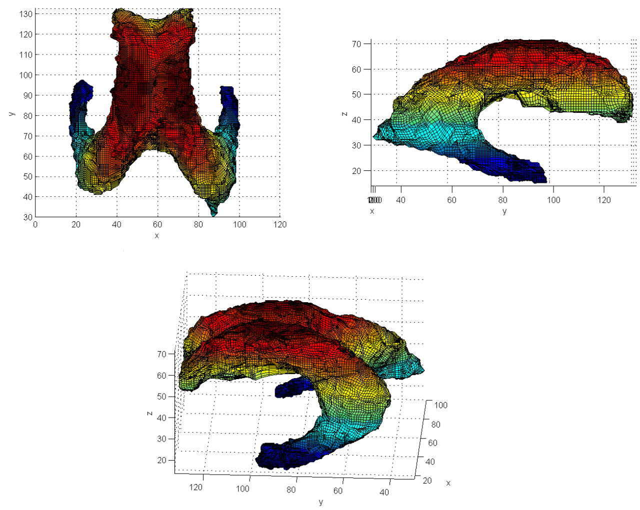


Fig. 4. Different view of the final result of human brain ventricle detection: (a) top view; (b) right view; (c) 3D view.

the deformation procedure; 2) we simplify the initialization step of the deformable model; 3) the geometric information of the object is utilized in the step of generating new surface patches from ”anchored” patches; 4) No topology transformation examination or implementation is needed in deformation steps. Further more, surface curvature adaptiveness is achieved in the proposed deformable model by associating the surface curvature with the size of the surface patches.

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