CENTER-POINT MODEL OF DEFORMABLE SURFACE

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Abstract: Center-point model of deformable surface for segmentation of 3D images is presented. Mobility of each node, element composing the surface, is constrained in the model to one direction. Also an original formula for image influence computation is proposed. The model aims at algorithm simplification and reduction of computational time needed for segmentation of 3D imaging data acquired from magnetic resonance or computer tomography scanner.

Key words: segmentation; deformable surface; center-point model

1. INTRODUCTION

Medical imaging techniques together with computerized image analysis revolutionized medicine. They have become important tools in medical diagnosis surgical planning and surgical simulation.

One of important image analysis operations is segmentation: a selection of image fragment representing objects of study such as an anatomical organ, its distinguishable part or pathological entity. In many cases these objects are oval and differ from surroundings with physical properties such as hardness or water content. Medical imaging techniques measure such physical properties and present them as a 2D or a 3D image, where the measurement is usually represented by gray-scale intensity. Therefore, image regions related to such objects differ from the background with their intensity.

The center-point model (CPM) of deformable surface is designed with this kind of images in mind. The CPM aims at computational simplification of segmentation algorithms based on deformable models and reducing computational time needed for segmentation of 3D images.

2. MODEL STRUCTURE

Deformable models for segmentation of digital images usually comprise nodes. Neighboring nodes are connected to form discrete curves[1] or surfaces[2, 3]. Image analysis using deformable models is a process of iterations – called matching process – which systematically displaces nodes and deforms the model structure to fit a boundary of object of interest.

Usual implementations of deformab1e model[1] assume that each node is assigned vector of coordinates in the space of the investigated image. In contrast to this idea, CPM node is assigned to fixed half-line[4]. Half-lines originate from an arbitrary chosen center point, are radiantly arranged and semi-equally spaced around this point. Thus, the position of every node s is given by its distance r_s from center point.

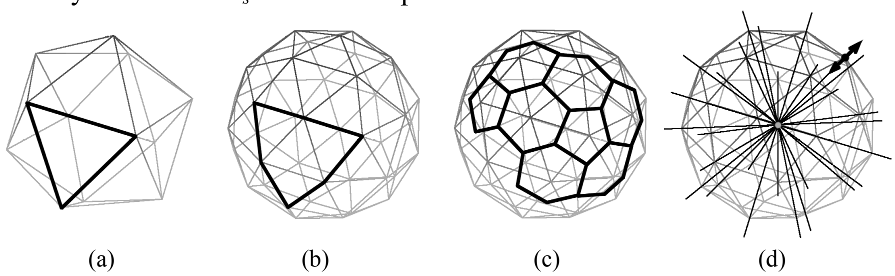


Figure 1. Tesselation of center-point model of deformable surface: icosahedron (a), first subdivision of icosahedron's faces (b), dual mesh with three-connected nodes (c), half-lines defining directions of nodes movement in center-point model

Tesselation of CPM surface is based on subdivision of icosahedron faces (figure 1.a). An icosahedron has a regular structure in an Euclidean 3D space. It has 12 vertices, where each vertex is connected to five other vertices forming 20 equilateral triangular faces. Consecutive subdivision of triangular faces of icosahedron[2] into smaller triangles (figure 1.b) increases the number and density of nodes or vertices. Every new vertex formed in this way is connected to six other vertices, while the original 12 vertices remain five-connected. However, also a dual (complementary) form of a mesh (figure 1.c), in which all the nodes are three-connected, may be applied. The center of resultant mesh structure is placed at the coordinates of an arbitrary chosen center-point. The half-line constraining the node movement begins in the center-point and contains one of the mesh vertices (figure 1.d).

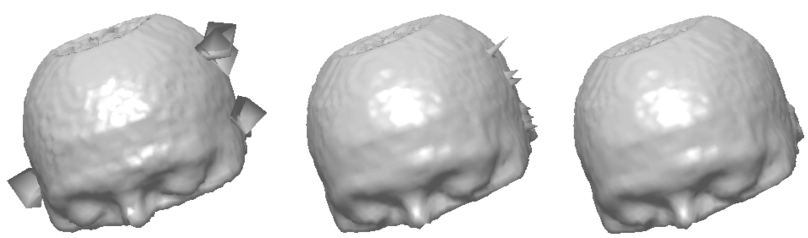
Choosing the right number of subdivisions and the number of nodes is computation time vs. final result resolution tradeoff. For application of MRI data segmentation 1000 – 3000 nodes seem adequate.

3. MATCHING PROCESS

The node has to be pushed toward desired position near the segmentation boundary. For this reason, an image influence vector is computed according to local properties of the image at node position. On the other hand, smoothness of deformable model must be retained, which is satisfied by modeling tension within surface. The deformable model matching is a process of successive nodes displacements intended for finding location where balance between image influence and internal tensions is obtained. The following three subsections describe the approach implemented in CPM.

3.1 Image Influence

In the current approaches nodes are usually attracted with large image gradient magnitudes. Hence, initial position of a deformable surface should be relatively close to the desired solution, i.e. "within range" of the gradient magnitude function slope. This problem is partly solved in a balloon model[6] where some "pressure" forces inflate the model and make it grow until its nodes reach locations of high gradient magnitudes. Unfortunately, if the intensity gradient of the boundary is small the balloon will grow without stopping at all. Moreover, balloon models are vulnerable to image artifacts and noise, which can cause them to fold and bend incorrectly (figure 2.a).



(a) (b) (c)

Figure 2. Examples of magnetic resonance imaging data segmentation with balloon model (α=0.02, β=0.001, ξ=0.02, τ=16, i=80) (a), center-point model and linear formula of tension computation (α=0.05, β=0, ξ=0.08, τ=16, i=25) (b), center-point model and formula of tension computation with linear and cubic components (α=0.05, β=0.001, ξ=0.08, τ=16, i=25) (c)

Let us assume that an object of interest differs from the image background with its brightness intensity and that some threshold value of intensity can be found, which roughly separates the object from its surroundings. Therefore, a simple formula of image influence force can be applied:

$$f_s = \xi\left(I(r_s) - \tau\right)$$

where ξ is a coefficient defining magnitude and turn of image influence force, $I(r_s)$ is an image intensity at coordinates of a node s and τ is the image intensity threshold. If the object is brighter than the image background, parameter ξ should be positive, otherwise negative. This way, force f_p pushes the node outside when the node is inside the object and pulls inside otherwise.

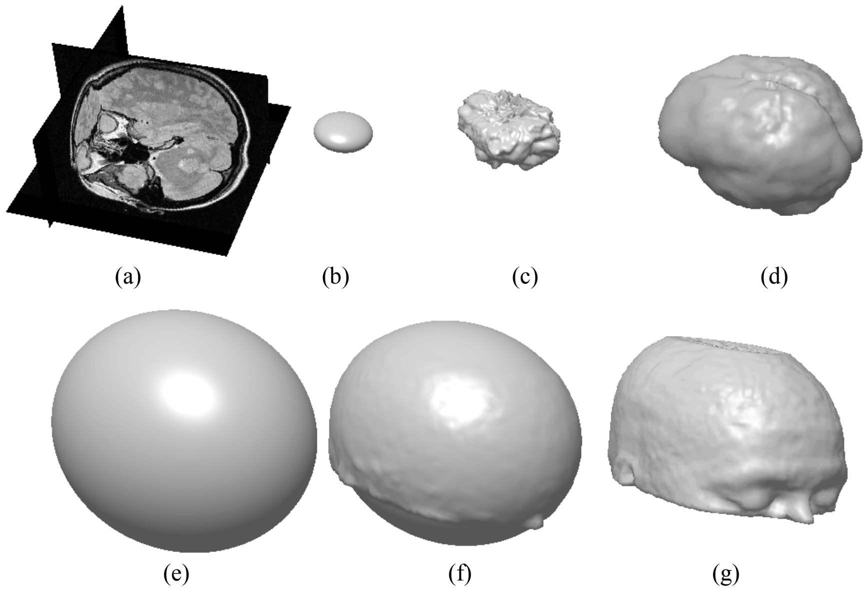


Figure 3. Phases of magnetic resonance data segmentation process with center-point model: cross-sections through input data (a), model initialized inside the object of interest (b), intermediate phase of matching process (c), result of cerebrum segmentation (ξ=0.06, τ=44, α=0.05, β=0.001, i=250) (d), initialization of surface surrounding the object (e), intermediate phase (f) and result of segmentation (α=0.05, β=0.001, ξ=0.08, τ=16, i=25) (g)

Consequently, there is no need for computation of an image gradient, which usually requires considerable computation time. Furthermore, the surface can be initialized in two ways: inside the object, to grow just like in balloon model, or it can surround the object at first and then shrink and tighten around it. This property is quite useful when two different objects, one inside another, are to be segmented (figure 3).

3.2 Tension

Tension is usually modeled by means of the thin-plate energy function[2, 5] or by the linear low-pass filtering of nodes coordinate vectors. In either case, the effective tension force influencing the node is a linear function of the node coordinates and coordinates of its neighbors.

Unfortunately, when applying the linear function for tension computation, some nodes tend to stop on local and strong image disturbances, such as MRI artifacts. Eventually, they produce spikes protruding from elsewhere-smooth surface (figure 2.b). To avoid such an effect, a nonlinear cubic component is added to the tension force formula. Still, the formula is simple and results in a reduction of computational time. The combined formula is:

$$g_s = \alpha\left(\frac{\sum_{n\in N_s} r_n}{\sum_{n\in N_s} 1} - r_s\right) + \beta\left(\frac{\sum_{n\in N_s} r_n}{\sum_{n\in N_s} 1} - r_s\right)^3$$

The equation consists of a linear and a cubic component, where N_s is a neighborhood of node *s*. The bracketed part is a difference between average coordinates of nodes within the neighborhood and coordinate of node s itself.

If an individual node is stopped on some image disturbance and it stays far from neighboring nodes, the nonlinear component causes neighboring nodes to pull it out much stronger than the linear component alone would do (compare figures 2.b and 2.c).

3.3 Node displacement

For simplicity the following equation for computation of node displacement is applied in CPM. An index *i* refers to discrete time.

$$r_s^{(i+1)} = r_s^{(i)} + g_s^{(i)} + f_s^{(i)}$$

4. RESULTS

The CPM of deformable surface was tested on biomedical images representing human head. Data was acquired from a MRI scanner. Results presented in figure 2.d and 2.g are obtained with CPMs composed of 1524 nodes. The process of segmentation requires 25 to 250 iterations (120 ms – 1.2 s using a PC with an Intel Centrino MT 1.6 GHz processor). The input data are comprised of 64 human head cross-sections, 256x256 pixels each, with 256 gray levels and ratio of voxel dimensions 1:1:2.

The CPM was compared with a balloon model. Tension force in a balloon model is computed with the same equation as proposed for CPM, with a coordinate *r* substituted by vector of 3D space coordinates. Also image influence force is computed the same way as for CPM. The direction of the force influencing the node is specified by average of normal vectors of faces including this node. It turned out that CPM is at least 20 times faster then the implemented balloon model. The reason is not only higher number of equations to be computed per iteration but also a requirement of decreasing image influence parameter ξ (usually 10 – 40 times) to prevent surface from undesired folding over (figure 2.a).

5. SUMMARY AND CONCLUSIONS

The problem of surface matching in CPM is reduced from 3D space to 1D space. In addition, the image influence formula is simplified. Consequently, the model is more efficient in comparison with models based on gradient computation.

The weaknesses of CPM are a prior need for knowledge on approximate center of volume to be segmented and limited complexity of shape that can be attained. Although the model is not limited to convex shapes and some concave shapes can be segmented, the best results are obtained for oval objects. However, in such case CPM can be useful for preliminary, rough segmentation providing valuable initialization data for other models producing more precise results.

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