



Bilateral Hermite Radial Basis Function for Contour-based Volume Segmentation

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Introduction

 Volume segmentation is fundamental – Extract information / Construct models

User interaction is necessary to segment ambiguous regions







Tumor in CT

Muscle in MRI

Organs in ISM

Interactive volume segmentation approaches





GraphCut, Region Growing, Active contours

<u>Slice-by-slice</u> Time consume ☺ Accurate

Contour-based

Moderate time Accurate

Seed-based

Easy & quick May cause error 🙁

Our goal

- Present a contour-based segmentation technique for ambiguous ROIs
- Generate segmentation boundary that

 pass through all contours
 have smooth shape around blurred image area
 fit to image edges around area with clear edges



Our approach

New technique based on implicit surface reconstruction



B-HRBF: New formulation to compute scalar field in bilateral domain

$$f(\overline{\mathbf{p}}_i) = 0, \quad \nabla f(\overline{\mathbf{p}}_i) = \mathbf{normal}$$
$$f(\overline{\mathbf{x}}) = \sum_i (\alpha_i \phi(\overline{\mathbf{x}} - \overline{\mathbf{p}}_i) - \beta_i \cdot \nabla \phi(\overline{\mathbf{x}} - \overline{\mathbf{p}}_i)) + \mathbf{a} \cdot \overline{\mathbf{x}} + b$$

Previous contour-based technique





Demo



B-HRBF segmentation

Overview

Gradient constraint

Contours \rightarrow constraint points & normals









2D gray scale image



Constraint

 points p_i
 normals n_i
 of boundary surface (curve in 2D)











Bilateral domain (3D)

Range (value) domain (1D)

Spatial domain (2D)





Scalar field $f(\bar{\mathbf{x}})$

 $f(\overline{\mathbf{p}}_i) = 0$

 $\nabla f(\overline{\mathbf{p}}_i) = \mathbf{normal}$

Bilateral-HRBF

 $f(\bar{\mathbf{x}}) = \sum_{i} (\alpha_{i}\phi(\bar{\mathbf{x}} - \bar{\mathbf{p}}_{i}) - \boldsymbol{\beta}_{i} \cdot \nabla \phi(\bar{\mathbf{x}} - \bar{\mathbf{p}}_{i})) + \mathbf{a}\bar{\mathbf{x}} + b$

Scalar field $f(\bar{\mathbf{x}})$

 $f(\overline{\mathbf{p}}_i) = 0$

 $\nabla f(\overline{\mathbf{p}}_i) = \mathbf{normal}$

We suggest the following kernels $\phi(\mathbf{x}) = ||\mathbf{x}||^{3}$ $\phi(\mathbf{x}) = ||\mathbf{x}||^{4} \log||x||$

Bilateral-HRBF

 $f(\bar{\mathbf{x}}) = \sum_{i} (\alpha_{i}\phi(\bar{\mathbf{x}} - \bar{\mathbf{p}}_{i}) - \boldsymbol{\beta}_{i} \cdot \nabla \phi(\bar{\mathbf{x}} - \bar{\mathbf{p}}_{i})) + \mathbf{a}\mathbf{x} + b$

intersection zero-set of $f(\overline{\mathbf{x}})$ & Image manifold

Image edges form steep slopes in image manifold Intersection of zero-set and image manifold often occur

- + Evaluate scalar field on image manifold $f(\mathbf{r}(\mathbf{x}))$
- + Extract zero set on image manifold $\{\mathbf{x}|f(\mathbf{r}(\mathbf{x}))=0\}$

+ Apply surface tracking marching cubes [SFYC*96]

s-D r-ch Image s-manifold in s+rD

2D grayscale

3D

2-manifold in (2+1)D

3-manifold in (3+3)D

3-manifold in (3+1)D grayscale

B-HRBF segmentation

Overview

Gradient constraint

Contours \rightarrow constraint points & normals

$$f(\overline{\mathbf{p}}_{i}) = 0$$

$$\nabla f(\overline{\mathbf{p}}_{i}) = \mathbf{normal}$$

$$f(\overline{\mathbf{x}}) = \sum_{i} (\alpha_{i}\phi(\overline{\mathbf{x}} - \overline{\mathbf{p}}_{i}) - \beta_{i} \cdot \nabla \phi(\overline{\mathbf{x}} - \overline{\mathbf{p}}_{i})) + \mathbf{a}\overline{\mathbf{x}} + b$$

Image manifold

- Normal is on tangent plane of image manifold
- Zero-set becomes near orthogonal to steep slopes of image manifold
- Intersection between zero-set and slopes of image manifold often occur
 - \rightarrow Edge fitting effect

 $\nabla f(\overline{\mathbf{p}}_i) = \begin{pmatrix} \mathbf{n}_i \\ \mathbf{0} \end{pmatrix}$

- Translate the spatial domain normal
- Zero-set is near orthogonal to spatial domain
- The shape of image manifold is unimportant
 - \rightarrow Smoothing effect

$$\nabla f(\overline{\mathbf{p}}_i) = \alpha \frac{\mathbf{J}\mathbf{n}_i}{||\mathbf{J}\mathbf{n}_i||} + (1 - \alpha) \begin{pmatrix} \mathbf{n}_i \\ \mathbf{0} \end{pmatrix}$$

Blend the two types of normals
 → Balance smoothing and
 →uv edge fitting effects

B-HRBF segmentation

Overview

Mapping normals

Contours \rightarrow constraint points & normals

0. Cross section & contour

- 1. Resample with an interval \mathbf{p}_i
- 2. Compute base normal as -

 $\mathbf{n}_i^0 = \mathbf{t}_i \times \mathbf{c}_i / ||\mathbf{t}_i \times \mathbf{c}_i||$ [HKHP11]

 \mathbf{t}_i : tangent of contour \mathbf{c}_i : normal of cross section

0. Cross section & contour

- 1. Resample with an interval \mathbf{p}_i
- 2. Compute base normal as - $\mathbf{n}_i^0 = \mathbf{t}_i \times \mathbf{c}_i / ||\mathbf{t}_i \times \mathbf{c}_i||$ [HKHP11]

The base normal has problem

Contours are orthogonal / slanted to target region

0. Cross section & contour

- 1. Resample with an interval \mathbf{p}_i
- 2. Compute base normal as - $\mathbf{n}_i^0 = \mathbf{t}_i \times \mathbf{c}_i / ||\mathbf{t}_i \times \mathbf{c}_i||$
- 3. Modify $\mathbf{n}_i^0 \rightarrow \mathbf{n}_i$ with heuristics

Use image gradient ∇I
Align base normal to ∇I

- Use intersection of contours
- Desired normal is $\mathbf{t}_l \times \mathbf{t}_m$

0. Cross section & contour

- 1. Resample with an interval \mathbf{p}_i
- 2. Compute base normal as - $\mathbf{n}_i^0 = \mathbf{t}_i \times \mathbf{c}_i / ||\mathbf{t}_i \times \mathbf{c}_i||$
- 3. Modify $\mathbf{n}_i^0 \rightarrow \mathbf{n}_i$ with heuristics

Normal \mathbf{n}_i avoid artifact even with slanted contours

Results

- Results were evaluated from experts

Right thigh segmentation (CT)

- 5 bones & 9 muscles
- Less than 30 min to segment each

Comparison with previous seed-based methods

- Tried to obtain same segmentation with three methods
- ROI has clear boundary (top) : all methods worked well
- ROI has blurred boundary (bottom): seed based methods failed

Comparison with previous contour-based method

Input contours

Our method

Previous method Implicit-surface reconstruction

Prev. method

Separated surfaces around shaftmiss edges around joint

Conclusion

- New volume segmentation technique
 - Compute scalar field in bilateral domain with B-HRBF
 - Define boundary as Intersection of zero-set and image manifold
- Acceleration scheme of B-HRBF (omitted)
- An contour-based user interface for segmentation

Thank you for your attentions

Limitation & future work

- To find good arrangement of contours is difficult for novices
- → To support to find nice contour arrangement

Bad example + unnecessary contours exist + additional contours required

Contour-based user interface is only for 3D
 → User interface for higher dimensional volume

Main bottleneck of algorithm

• When computing BHRBF

$$f(\overline{\mathbf{x}}) = \sum_{i} (\alpha_{i} \phi(\overline{\mathbf{x}} - \overline{\mathbf{p}}_{i}) - \boldsymbol{\beta}_{i} \cdot \nabla \phi(\overline{\mathbf{x}} - \overline{\mathbf{p}}_{i})) + \mathbf{a}\overline{\mathbf{x}} + b$$
$$f(\overline{\mathbf{p}}_{i}) = 0, \qquad \nabla f(\overline{\mathbf{p}}_{i}) = \mathbf{normal}$$

We have to solve dense and large linear system

 We solve the linear system by LU-factorization based method ← this is the main bottleneck

Acceleration of LU factorization

stored contour (fixed)

Active contour (can be change)

- User edits only one contour at a time
- Matrix consists of 2 parts (correspond to active/stored contour)
- Pre-compute LU factorization of stored contour part
- Compute LU factorization only a part correspond to active contour

Correspond to stored contour

Acceleration of LU factorization

• All contours are stored and we factorized HRBF matrix in LU form

- The user may select a contour to activate (to re-edit)
- HRBF matrix consists of two part
 - Correspond to activated contour / stored contour
- We sweep a part correspond to active contour to right bottom keeping a the LU form [Gondzio's algorithm]

