Deformable Organ Contour Transfer with Deep Inverse Shape Encoding (DISE) Networks for Auto-segmentation in Low Contrast Regions

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Purpose: Robust automatic segmentation of thoracic and abdominal CT images with low CNR

Method: Deep Inverse Shape Encoding (DISE) networks
   ○ Inverse Shapes for coarse regional partition
   ○ Sparse registration via shape matching
   ○ Reference guided labeling

Results and Evaluation
Introduction: Automatic segmentation

Existing automatic methods: based on dense voxel-wise registration using

- **patch texture**\(^1\)
- **gradients**\(^2\)

Shortcomings:

- **Time consuming**
- **Not robust to low CNR images**

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\(^1\) Korfiatis et al. IEEE Trans Inf Technol Biomed, 2010
\(^2\) Sotiras et al. IEEE TMI, 2013
\(^3\) Liu et al. SU-K-201-14 (Snap Oral), AAPM 2017
Robustly, automatically segment CT (CBCT) images of thoracic, abdominal regions with low CNR

To replace manual delineation and segmentation based on dense registration
Method: deep inverse shape encoding (DISE) network

Deep Inverse Shape Encoding (DISE) Network

- **Reference CT Image**
  - Reference Inverse Shapes
  - Induced by Intensity Binning
  - Reference Shape Descriptors
- **Target CT Image**
  - Target Inverse Shapes
  - Inverse Shape Encoding
  - Target Shape Descriptors
  - Corresponding Target Descriptors
  - Multi-layer Sparse Shape Matching

Reference CT with provided ROI Contours
Target CT with automatically Generated Contours
Inverse shape: basic concept with 2D illustration

Gradient:
\[ \nabla I(x_0) \approx \frac{I(x_0 + \Delta x)}{\Delta x} \]

- Local in spatial support
- Non-robust to noisy change in intensity

Inverse Shape:
\[ \text{invShape}(l_0, \Delta l) = \{ x | I(x) \in [l_0, l_0 + \Delta l] \} \]

- Non-local in spatial support
- Robust in shape to noisy change in intensity
Illustration: inverse shape on XCAT phantom

Five inverse shapes\(^1\) are shown by their boundaries, each in a unique color.

Illustration: sparse samples on a pair of inverse shapes

Sparse samples on inverse shape containing liver, spleen, diaphragm and aorta
5064 samples (from 1.34M voxels) on reference, 5059 samples (from 1.33M voxels) on target
Shape encoding via shape context descriptor\(^1\) (2D)

Reference

- Log-polar histogram of samples on the shape
  (equally-spaced bins along circumference, larger radii bins at coarser scale)
- Capture topology at multiple scales

Target

\(^1\) Belongie et al. IEEE PAMI 2002
Inverse shape encoding via shape context descriptors (3D)

Geometric depiction

data structure for shape descriptor

3D Shape context descriptor in log-spherical histograms
DISE network for inverse shape matching

Reference
Inverse Shapes

Reference
Shape Descriptors
Layer 1
$r_{\text{max}} = R_1$

Layer 1
Matching

Target
Shape Descriptors
Layer 1
$r_{\text{max}} = R_1$

Initial

Reference
Shape Descriptors
Layer 2
$r_{\text{max}} = R_2 < R_1$

Layer 2
Matching

Target
Shape Descriptors
Layer 2
$r_{\text{max}} = R_2 < R_1$

Refinement

Reference
Shape Descriptors
Layer L
$r_{\text{max}} = R_L < R_{L-1}$

Layer L
Matching

Target
Shape Descriptors
Layer L
$r_{\text{max}} = R_L < R_{L-1}$

Final Match Result
Correspondence between shape descriptors $\rightarrow$ matching between inverse shapes
Results and Evaluation: liver contour transferring

- XCAT Phantom
- Fast, robust segmentation by DISE network
- DSC on Liver: 0.98
  \[ DSC = \frac{2|V_{gen} \cap V_{gt}|}{|V_{gen}| + |V_{gt}|} \]
- Robust to noise

Results and Evaluation: liver contour transferring

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Liver contour on reference image

Generated liver contour on target image

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Summary of DISE network

- Achieve both robustness and efficiency for anatomical segmentation:
  - Coarse partition of image domain into inverse shapes induced by intensity bins
  - Sparse representation of the inverse shape via sparse sampling and shape context descriptor
  - Contour transfer
    - Shape matching via DISE network
  - Can facilitate finer registration and other analysis tasks
Thank you!

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3D shape matching via two layer coding.

S. Belongie, J. Malik, and J. Puzicha.
Shape matching and object recognition using shape contexts.
A. M. Bronstein, M. M. Bronstein, and R. Kimmel.  
**Rock, paper, and scissors: extrinsic vs. intrinsic similarity of non-rigid shapes.**  

**Deep view morphing.**  
**Digital anthropomorphic phantoms of non-rigid human respiratory and voluntary body motion for investigating motion correction in emission imaging.**
*Physics in Medicine & Biology, 59(14):3669, 2014.*

**Robust automatic co-segmentation of multiple medical images.**
SU-K-201-14, presented at AAPM 2017.
O. Nomir and M. Abdel-Mottaleb. 
Hierarchical contour matching for dental X-ray radiographs. 

Covariance descriptors for 3D shape matching and retrieval. 

Y. Zhang, F.-F. Yin, W. P. Segars, and L. Ren. 
A technique for estimating 4D-CBCT using prior knowledge and limited-angle projections. 