A non-local Chan-Vese model for sparse, tubular object segmentation

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Context: ANR project VivaBrain\textsuperscript{1}

3D MRA
Medical teams

Segmentation
Computer Science teams

Blood flow simulation
Mathematics teams

Meshing
Simulation

Problem formulation

\[ f(x) = \Phi(x) + \sum_{i=1}^{R} \psi_i(V_i x) + \psi_{\omega 0}(x) \]

- \( \Phi(x) \) is a sum of data fidelity term
- \( \Phi(x) = \sum_{i \in \mathbb{R}} \phi_i(y_i - u_i) + \sum_{i \in \mathbb{R}} \varphi_i(x - 1) \phi(y_i - u_i) \)
- \( u_i^0 = \text{Quantiles}(\chi_0), \delta \) and \( u_i^1 = \text{Quantiles}(\chi_1), 1 - \delta \)
- \( \sum_{i=1}^{R} \psi_i(V_i x) \) a hybrid regularization term
- \( \psi_{\omega 0}(x) \) an indicator function of a convex subset of \([0, 1]^N\)

Optimization approach

Let \( f \in \Gamma_0(\mathbb{R}^N) \) (lower semi-continuous proper convex function). For every \( x \in \mathbb{R}^N \), the minimization problem consists of finding

\[ \text{prox}_{\mathbb{R}^N}(x) := \arg\min_{y \in \mathbb{R}^N} f(y) + \frac{1}{2} \| x - y \|^2 \]

Proximal method: Primal-dual algorithm [Combettes and Pesquet, 2012]
- convergence guaranteed
- incorporating any Lipschitz differentiable function \( \varphi \) and arbitrary linear operators \( V_i x \)

Drive database results (20 images)

<table>
<thead>
<tr>
<th>TPR</th>
<th>Sensitivity</th>
<th>SPC</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human</td>
<td>0.780</td>
<td>0.719</td>
<td>0.679</td>
</tr>
<tr>
<td>Staal</td>
<td>0.977</td>
<td>0.977</td>
<td>0.980</td>
</tr>
</tbody>
</table>

Conclusions

Statistical non-local centroids:
- simplicity
- well adapted to angiographic images

Primal-dual algorithm:
- high flexibility
- robust to computational errors

Future work:
- efficient implementation of the proposed algorithm
- add connectivity and tubularity priors
- variational framework for multi-scale segmentation

\textsuperscript{\textdagger} \text{http://vivabrain.fr}

Segmentation: Angiographic Images

Difficulties:
- To extract some small tubular structures of lower intensity in the presence of:
  - low contrast
  - noise
  - background/foreground inhomogeneity
  - sparse object

Inhomogeneity of object and background

\( \omega_0 = \text{background and } \omega_1 = \text{intensity inside object} \)

Experiments: VascuSynth and DRIVE database results

<table>
<thead>
<tr>
<th>Original (max. projection view)</th>
<th>Ground truth</th>
<th>Piecewise const. ((0.753, 0.984))</th>
<th>Ours ((0.853, 1.000))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original (max. projection view)</td>
<td>Ground truth</td>
<td>Human ((0.797, 0.972))</td>
<td>Ours ((0.800, 0.936))</td>
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</tbody>
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