Texture-based graph regularization process for 2D and 3D ultrasound image segmentation

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Introduction
Two requirements for a successful image segmentation algorithm are the availability of meaningful pixel characteristics and the ability to compare pixels efficiently. Most algorithms operate on gray-level intensities and compare pixels to their closest neighbors, which is too basic to deal with complex vision problems. Here, we propose to combine two “non-local” approaches. The first relies on using texture characteristics, which allows to describe each pixel within its environment, while the second one applies a regularization process on a graph representing the image (Ta 2009), whose structure allows to express relations between any pair of pixels. Applied on ultrasound images, and compared to the original graph-regularization algorithm, our method shows an improvement of the quality of segmentation.

Segmentation by graph regularization

An image is represented by a similarity graph \( G = (V, E, w) \), each node being associated to a pixel.

The \( f_i \) function maps each node to a vector of real values, the characteristics of the associated pixel. This vector can be any combination of pixel’s characteristics: coordinates, grayscale/color intensities, or higher level characteristics, such as texture features.

An heuristic is then used to connect similar nodes together, and a measure of the similarity of two connected nodes is used as the weighting function \( w \) of the graph.

The segmentation is obtained by regularizing \( f \), a membership function characterising the segmentation, while minimizing the following energy:

\[
\mathcal{E}(f, b) = R_w(f) + \sum_{u \in V} g(b, u)f(u)
\]

The first term evaluates the regularity of the segmentation:

\[
R_w(f) = \sum_{u \in V} \sum_{v \sim u} \sqrt{w_{uv}}|f(v) - f(u)|
\]

Where \( V \) is the set of nodes, and \( v \sim u \) denotes a neighborhood relation between two nodes of the graph.

The second one is the fitting term, \( g() \) being the fitting criteria. Based on the work of Ta and Chan & Vese, we propose a criteria adapted to vector-valued images:

\[
g(b, u) = \frac{1}{M} \sum_{i=1}^{M} \left( \lambda_1 (q_{1,i} - b_1(u))^2 - \lambda_2 (q_{2,i} - b_2(u))^2 \right)
\]

Where \( q_{1,i} \) and \( q_{2,i} \) represent the average value of the characteristics \( i \) inside \( f = 0 \) and outside \( f = 1 \) of the segmented region, and \( M \) is the number of characteristics.

A relaxed version of this energy is then minimized by using a Gauss-Jacobi iterative algorithm.

Experimental results

Our method is evaluated on a set of ultrasound images, ultrasonography being an imaging technique known to be particularly noisy. Some Haralick features (Haralick 1973) are used as a source of textual information. Results are shown in the table below.

Graphs being data structures able to represent any discrete data, our algorithm can process 2D images without any modification.

<table>
<thead>
<tr>
<th>Image</th>
<th>Our méthode</th>
<th>C &amp; V</th>
<th>Vector-valued C &amp; V</th>
<th>Ta</th>
</tr>
</thead>
<tbody>
<tr>
<td>echo1</td>
<td>1.82%</td>
<td>2.41%</td>
<td>3.45%</td>
<td>8.31%</td>
</tr>
<tr>
<td>echo2</td>
<td>2.02%</td>
<td>3.28%</td>
<td>1.25%</td>
<td>N.A.</td>
</tr>
<tr>
<td>echo3</td>
<td>1.86%</td>
<td>7.16%</td>
<td>3.26%</td>
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</tr>
<tr>
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<td>3.77%</td>
<td>3.34%</td>
<td>4.90%</td>
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<tr>
<td>echo5</td>
<td>2.62%</td>
<td>3.39%</td>
<td>3.62%</td>
<td>10.69%</td>
</tr>
<tr>
<td>echo6</td>
<td>2.16%</td>
<td>3.07%</td>
<td>3.14%</td>
<td>3.40%</td>
</tr>
</tbody>
</table>

Percentage of misclassified pixels (according to a groundtruth.)

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