Fast registration of segmented images by normal sampling

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ABSTRACT
It is known that image registration is mostly driven by image edges. We have taken this idea to the extreme. In segmented images, we ignore the interior of the components and focus on their boundaries only. Furthermore, by assuming spatial compactness of the components, the similarity criterion can be approximated by sampling only a small number of points on the normals passing through a sparse set of keypoints. This leads to an order-of-magnitude speed advantage in comparison with classical registration algorithms. Surprisingly, despite the crude approximation, the accuracy is comparable. By virtue of the segmentation and by using a suitable similarity criterion such as mutual information on labels, the method can handle large appearance differences and large variability in the segmentations. The segmentation does not need to be perfectly coherent between images and co-segmentation is acceptable.

We demonstrate the performance of the method on a range of different datasets, including histological slices and Drosophila imaginal discs, using rigid transformations.

OVERVIEW
Goal
• Fast approximative image registration

To make it fast
only consider
• class — use segmented images
• neighborhood of class boundaries
• motion normal to boundaries

PROBLEM DEFINITION
Find a transformation
\[ T = \arg \max_{T} J(T) \]
with
\[ J(T) = \int f(x) \log f(T(x)) \, dx \]
for segmented images \( f, g \).

Mutual information on labels (MIL) similarity criterion
\[ \psi(f, g) = \max_{T} \int \log \left( \frac{f(x)g(T(x))}{\mu_f(x)\mu_g(T(x))} \right) \, dx \]
with
\[ \mu_{f,g}(x) = \left\{ \begin{array}{l l} 1 & \text{if } f(x) + g(T(x)) > 0 \\ 0 & \text{else} \end{array} \right. \]
\[ \psi_{f,g} = \sum_{u,v} \psi_{u,v} \]
\[ N_{f,g} = \sum_{u,v} \psi_{u,v} \]

WHAT TAKES TIME IS MOSTLY THE PREPROCESSING
Superpixels e-means Precompute Registration Total

<table>
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<tr>
<th>Method</th>
<th>Time (s)</th>
<th>( \mu_{f,g}(x) )</th>
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| REFERENCES |