A multi-agent framework for MRI brain scans segmentation

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Purposes
We are interested in the segmentation of MRI Brain scans. Image segmentation is intrinsically a distributed process in term of goals to be reached, of zones in the image to be processed and of treatments to be achieved. Face to the general complexity of images (i.e. variability of anatomical structures and acquisition artifacts such as noise, intensity non-homogeneities or partial volume effect) the focalizations are continuously reconsidered during the evolution of the segmentation process. We advocate situated and cooperative agents as a framework to manage the various information processing steps required in this context.

Method
Situated and cooperative agents borrow from reactive artificial intelligence the principle of autonomy, each agent acquiring autonomously the knowledge needed to reach its own goal, from situated cognition, the principle of contextual localization, each agent being situated in a local evolutive context with specific neighborhood constraints to preserve the global consistency of the segmentation process and from multi-agents theory, the principle of cooperation, each agent interacting with its acquaintances to reach its goal. Three types of agents, each with a specific role, coexist in our system: global and local control agents and tissue dedicated agents. The global control agent partitions the data volume into adjacent territories (30 voxels side cubes approximately), and then assigns to each territory one local control agent. The local control agents create tissue dedicated agents, estimate model parameters and confront tissue models for labeling decision according to two phases: an under-segmentation phase where only the most reliable voxels are labeled and a final phase where tissue model are re-evaluated (mainly at tissue frontiers) before labeling the remaining voxels. The tissue dedicated agents execute tasks distributed by tissue type, typically the interpolation of tissue model from the neighborhood and the labeling of voxels using a region growing process. Local control agents and tissue dedicated agents interleave locally (inside each cube) several behaviors (EM gaussian mixture estimation, region growing …). Agents activities have to be coordinated inside a given volume partition or between neighboring partitions, function of the available and incrementally extracted knowledge. Depending of the progress of the segmentation task, tissue dedicated agents from neighboring cubes interact during their model control behavior and during their region growing behavior. The agents share a common information zone organized according to the tissue types and spatial relations.

Results
MR images generated by the BrainWeb simulator [1] have been used to quantitatively evaluate the proposed method. Starting with images whose tissue classification was perfectly known, we created images with several noise levels (3%, 5% and 7%) and bias field non uniformities (0%, 20% and 40%). We calculated for each tissue, true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN) voxels classification, and then the Jaccard coefficient (TP/(TP+FP+FN)). Results are shown in Table 1.

Table 1. Results on Brainweb phantom

<table>
<thead>
<tr>
<th>n = 3%</th>
<th>n = 5%</th>
<th>n = 7%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20%</td>
<td>40%</td>
</tr>
<tr>
<td>WM</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td>GM</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Figure 1. Illustration of the segmentation process. 1a shows the initial image and the cubic partition (white square) where the local histogram shown in 1d was computed. The GM peak was missing due to the presence of a sub-cortical structure. Based on models present in the neighborhood this peak was computed (1e) and the initial image was under-segmented (1b). During the final phase, the refinement of the radiometric model was computed (1f) and the final segmentation is present in 1c.

Discussion
Results are comparable to other methods relying on markov random field models, including a bias field correction map and following an optimal strategy [2], with a lower computational burden (less than 5 min to segment a complete volume). Our framework is extensible: new qualitative information maps can be introduced to efficiently add and share complementary information such as anatomical knowledge for structures labeling. It constitutes a part of a larger software for fMRI retinotopic mapping [3].

References