Situated Cooperative Agents: a Powerful Paradigm for MRI Brain Scans Segmentation

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Abstract. To cope with the difficulty of 3D MRI brain scans segmentation, specification and instantiation of *a priori* models should be constrained by local images characteristics. We introduce *situated cooperative agents* for the extraction of domain and control knowledge from image grey levels. Their dedicated behaviours, i.e segmentation of one type of tissue, are dynamically adapted function of their position in the image, topographic relationships and radiometric information gradually gained during local region growing processes. Acquired knowledge is gathered and shared via qualitative maps. Incremental refinement of the segmentation is obtained through the combination, distribution and opposition of solutions concurrently proposed by the agents.

1 INTRODUCTION

Image interpretation consists in finding a correspondence between radiometric information and symbolic labelling with respect to specific spatial constraints. This requires the specification and instantiation of *a priori* models of the structures to detect. Face to the general complexity of images, several descriptors are defined and merged, learning phases are introduced and cooperation between several image processing stages are used. We are interested in medical image processing especially Magnetic Resonance Imaging (MRI) brain scans interpretation. Functional MRI (fMRI) is a recent non invasive and indirect technique for the detection of brain activation in response to specific stimuli. Measured activity is mainly located in the grey matter, a 2D ribbon structure highly folded in the brain. Then, a rationale way to visualize and analyse activity maps consists in unfolding the grey matter [1]. Flattened or unfolded maps display the activity buried in cortical sulci while preserving some aspects of spatial relationships. The quality of anatomical scan segmentation is crucial for unfolding because small errors, for instance in fine structures such as sulci, lead to large distortions on unfolded maps [2].

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Anatomical brain scan segmentation is a challenging application for several reasons: 1) huge data volume (≈10Mb for one 3D image), 2) high variability and low specificity of classes characteristics due to image acquisition artefacts, 3) presence of complex objects structures such as sulci and 4) high variability of spatial relationships and objects forms due to individual anatomy variability.

The purpose of this paper is to demonstrate the potential interest of *situated agents* for MRI brain scans interpretation. Situated agents borrow 1) from reactive AI the principle of *autonomy*, each agent acquiring autonomously the knowledge necessary to reach its own goal and 2) from situated cognition [3], the principle of *contextual localization*, each agent being situated in a local evolutive context with specific neighbourhood constraints to preserve the global consistency of the segmentation process. Agents run in a cooperative framework, where cooperation is not envisaged as usual for communication purposes only but as a mean for 1) *rooting* the agents: the position of each agent is adapted depending on the current state of the global segmentation process, 2) *referencing*: each agent modifies its local model depending on those built by neighbouring agents, and 3) *controlling*: segmentation is performed incrementally through the combination, distribution and opposition of solutions concurrently proposed by the agents.

In the remainder of the paper, we position in Section 2 our approach with respect to the literature. In Section 3, we detail the situated agents environment and report in Section 4 the results obtained using realistic phantoms. Then, we discuss in Section 5, several aspects of our work and point out work under development.

2 MRI BRAIN SCAN SEGMENTATION: RATIONALE

Brain segmentation consists in three steps: 1) skull stripping to keep only brain tissue from MRI, 2) compensation for the non uniformity of the grey levels for each tissue (shading artefact) and 3) labelling of each voxel. We focus our paper on this last point and consider the labelling of grey matter (GM), white matter (WM), and cerebo spinal fluid (CSF). Labelling is a particularly difficult step due to partial volume effect. It is achieved through boundary-finding or region-based approaches, or the fusion of both [4 , 5]. In our context, boundary-finding can be based on active shape models [6] where the model of the

object to detect (GM ribbon) is derived from a learning set and then deformed to fit the specificity of a new object. However, the use of global constraints hampers the delineation of fine structures such as sulci. Automatic extraction of the inner and remains an open-problem. Our approach pertains to the region-based approaches. The underlying Bayes formula, common to these approaches, yields maximum *a posteriori* (maximum likelihood) classifier. The prior probabilities can be set by the user [8], based on an atlas [9] or on the relative frequency of each class in the volume [10, 11]. The likelihood of a particular voxel v_i belonging to a certain tissue t_i is generally modelled as a normal distribution [12] whose parameters ($<\mu_t>$, $<\sigma_t>$) have to be estimated. Different techniques can be used in this respect like fuzzy K-means [13] or the E/M algorithm applied locally [10] or globally [14] over the volume image.

Two strategies to drive the global segmentation process can then be applied: incremental or iterative. When labelling is realize step by step for each tissue (incremental strategy), *a priori* knowledge is introduced to *control* the process and *initialise* each step. In [8, 15, 16], the authors exploit the fact that intensity levels of WM have smaller intensity variability than GM (in T1 weighted scans) and that GM surrounds WM. Then, GM is automatically created by a constrained growing process from WM. In [17] morphological operators delineate a sulci mask from which a growing process is launched to determine the GM. In [4], the use of a deformable model allows to position accurately seeded-region-growing agents that firstly segment GM. From GM ribbon, a second agent population is launched to segment WM. Clearly, in these approaches, the quality of segmentation at a given step depends on the quality of segmentation at previous steps. Conversely, as regards iterative strategy, the Markov random field (MRF) approach can be used to introduce, via a regularization term, spatial and anatomical constraints. Labelling is then obtained through the iterative minimization of some given energy function. Here again, initialisation is a crucial step for MRF parameter estimation. It may be realized by fitting an histogram over the image volume [18], using K-means and E/M classification [19], maximum likelihood classification [20], or using prior classification derived from a digital brain atlas [21]. Estimation and labelling are generally processed sequentially but can be combined in a global iterative process [21].

Based on this brief analysis of the literature, it appears that major issues, from the application viewpoint, are to preserve fine structures such as sulci, limit manual corrections by the user and be computationally efficient. Major issues, from the technical viewpoint, are (i) to proceed to proper initialisation of the segmentation process, (ii) to proceed to adequate modelling of the tissue statistics and (iii) to derive a strategy allowing the confrontation and fusion of the segmentation results. At the light of the methods cited above, the main statements of our methodology are 1) to work locally to cope with grey level non uniformity, 2) to manage neighbourhood information to keep control of local processes via global information (although MRF is a powerful model for defining a formal neighbourhood system, small image details are generally lost), 3) to segment outer surfaces of the cortex can be modelled as a front propagation problem solved using level set techniques [7]. Manual placement is required for the initialisation of the algorithm and computational efficiency

concurrently the various tissues to gain mutual constraints from their confrontation and 4) to adopt a constructivist approach based on successive refinements, to cope with the fact that parameter estimation is a local and error-prone process. Situated agent is the computational paradigm of this methodology.

3 SYSTEM DESIGN

3.1 Rationale

The grey level distribution over the brain tissues is modelled as a mixture of gaussian distributions, whose parameters have to be estimated from the available data, to minimize the *a priori* needed to launch the segmentation process. Due to the high variability of the grey level information through the image volume and to gain in precision, the estimation is performed on a local basis. As estimation is an error-prone process, the models are confronted and adjusted in several steps to augment their local consistency and to ground them more deeply in the available data. An illustration of this process is shown in Figure 1.

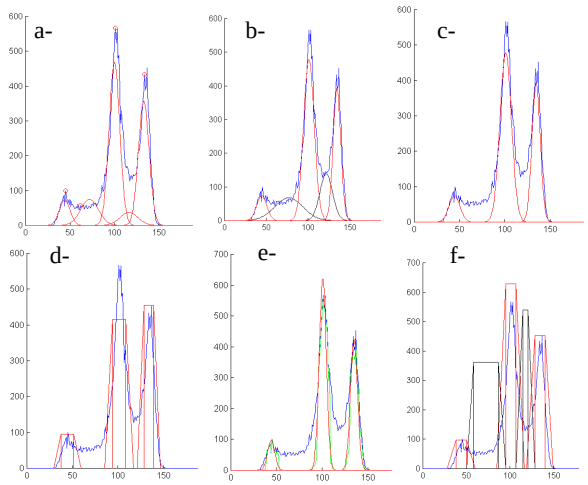

Figure 1. Data model estimation: a) initialisation step (looking for the histogram modes), b) E/M for modelling normal tissue distributions, c) adjustment of the model using the neighbourhood, d) fuzzyfication, e) distribution re-estimation after labelling, f) computation of new membership functions (introduction of partial volume effect modelling).

As labelling is also an error-prone process, it is performed locally, by dedicated agents, according to an incremental strategy. A region growing process is used, starting from a carefully selected seed, in order to aggregate the highly confident pixels first. This process evolves in three steps (see Figure 2): 1) firstly, hard grey level constraints are used, and then 2) they are relaxed and combined with topological constraints and finally 3)

a competitive approach is used to label the remaining voxels. Three complementary forms of cooperation are therefore combined in an incremental data processing strategy [11]: augmentative cooperation, according to which the data volume is partitioned into zones processed by local agents, confrontational cooperation, according to which the results obtained by the agents results (models as well as voxel labels) are confronted and compared, integrative cooperation, according to which the problem solution is obtained through successive coordinated data processing steps.

Figure 2. Snapshots of the segmentation process: a) result of the first segmentation step, b) second segmentation step: relaxing the grey level constraint and using a topological criteria, c) third segmentation step: confronting the labels for remaining pixels at the frontier between tissues.

3.2 Architecture

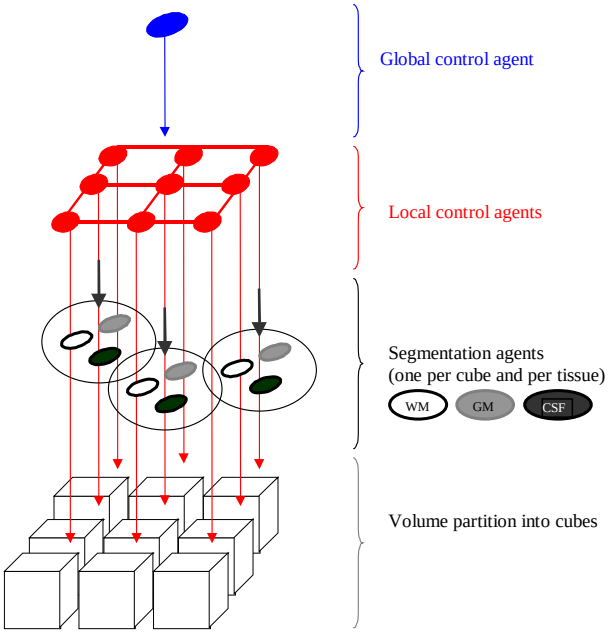

Figure 3. Three types of agents exist in the system: global and local control agents, whose the role is to build the processing model of the system, and segmentation agents, whose the role is to cooperatively label the data volume.

The system is made of agents running under control of a scheduler, whose role is to manage their creation, destruction, activation and deactivation. Each agent is in turn provided with several behaviours running under control of a dedicated scheduler. The launching of a given agent or behaviour is context-dependent, as driven by a simple synchronization model. The agents are organized into groups [22] running under control of a manager which ensures their proper coordination. The agents share a common information zone, organized according to the tissue types and spatial relations, and storing global and local statistical information. Qualitative information maps are introduced to efficiently gather, retrieve and easily add complementary information such as tissue membership values or topological relations.

3.3 Agents Roles and Behaviours

Three types of agents coexist in the system (Figure 3): global and local control agents and segmentation agents. The role of the global control agent is to partition the data volume into adjacent territories, and then assign to each territory one local control agent. The partitioning can be iterated several times to focalise local control agents on problematic regions such as tissue frontiers, sulci or ventricles. At the beginning, the volume is partitioned into adjacent cubes and each local agent is provided with global statistical information about MRI brain scans.

The role of local control agents is to estimate and adjust the local statistical models given to segmentation agents, to create and launch them and refine the final segmentation result. More precisely each local agent articulates the following behaviours:

- LcA1: Computation of local statistical models and segmentation agent creation: based on E/M algorithm, the issue is to extract, from the data pertaining to each territory, the distribution model (see Figures 1-a, 1-b). Segmentation agents are then created, one per territory and per tissue, provided with the local distribution when available.
- LcA2: Computation of tissue membership functions: fuzzy functions are computed for each tissue distribution and mutually adjusted to avoid superposition (see Figure 1d). In order to favour highly confident voxels, the segmentation agent rooting behaviour is selected only if sufficiently robust membership functions are obtained. Otherwise, region growing is started eventually from pixels located at tissue frontiers and selected by neighbouring agents (information diffusion).
- LcA3: Model adjustment behaviour: the issue is to re-evaluate the initially computed distribution models, based on the labelling performed by the segmentation agents (see Figure 1-e).
- LcA4: Segmentation completion: to allow for more specificity in the segmentation process evaluation, new membership functions are computed, corresponding to partial volume effects (see Figure 1-f). All remaining non-labeled pixels are ordered in a common list, according to their membership degree, and labeled to the most probable tissue.

Three types of segmentation agents are distinguished, whose role is respectively to segment GM, WM and CSF. More precisely each segmentation agent articulates the following behaviours :

- SA1: Refinement of the gaussian model: the issue is to refine the distribution model computed by the local control agent, based

on neighbouring distributions for the same tissue (see Figure 1-c). An interpolation process is used to replace, when departing from the interpolated values, the initially computed gaussian model. The process is iterated until stabilization of all agents to cope with the fact that at a given time some distribution models may be lacking for some neighbouring agents.

- SA2: Rooting behaviour: the issue is to compute a rooting location for the agent. The search for this location is iterated, from the centre of the zone to its periphery, until some local satisfaction criteria is reached. If no location is found, the region growing behaviour is selected and runs eventually on candidate pixels placed at the frontiers and selected by neighbouring agents.
- SA3: Region growing behaviour: this behaviour proceeds in two coordinated steps: hard radiometric constraints are used first, and relaxed in a second step where they are combined with topological information. Candidate pixels, e.g. non-labelled pixels connected to the currently labelled pixel, are marked along this process. If these pixels reach the frontier with a neighbouring territory, they are stored into the candidates list of the corresponding agent, which is automatically reactivated, if inactive, to process them.

3.4 Agents Coordination

Gradual refinement of tissue distribution models interleaves local control agent behaviours with segmentation agent behaviours. The following loop combines the different behaviours: LcA1, SA1, LcA2, SA2 or SA3, LcA3, SA1 and LcA4. The firing of local control and segmentation agent behaviours alternates. This coordination is controlled by the agents themselves through a shared variable representing task completion. When this global variable is decremented to 0 by a given agent, this agent reactivates the agent group whom it is member. Reactive capabilities are also provided to the segmentation agents to manage two situations: 1) refinement of the gaussian model is fired for a given agent, each time one of its neighbours modifies its own model, 2) the growing behaviour is fired (and rooting behaviour is stopped if any) for a given agent, each time new pixels are provided as candidate pixels by neighbouring agents. Reactivity is a central point in our approach as it allows information diffusion on the fly of the segmentation process and limits the search for rooting.

4 RESULTS

To quantitatively evaluate our method, we used MR images generated by the BrainWeb simulator [23]. Starting with images whose the tissue classification was perfectly known (considered as our reference for each tissue i.e. Ref masks), we created using BrainWeb images with several noise levels (3% , 5% and 7%) and bias field non uniformities (20% and 40%). For these six images, we compared the results obtained with our method to those obtained with two methods based on MRF and including shading effect correction [9, 21]. For this purpose, we computed for each tissue the Jaccard similarity, equivalent to the Tanimoto coefficient and equal to TP/(TP+FP+FN), between Ref masks and masks obtained by the three methods. The results of this evaluation are represented in Table 1. Some results provided by other methods are reported in [20].

Table 1. Results on Brainweb phantom

		n = 3%		n = 5%		n = 7%	
		20%	40%	20%	40%	20%	40%
∇	WM	0.88	0.87	0.87	0.86	0.86	0.81
	GM	0.89	0.89	0.87	0.87	0.81	0.82
◊	WM	0.84	0.85	0.83	0.83	0.78	0.78
	GM	0.87	0.87	0.82	0.82	0.78	0.78
Δ	WM	0.92	0.90	0.88	0.86	0.82	0.82
	GM	0.91	0.90	0.86	0.86	0.80	0.81

∇ SPM[9] , ◊ [21], Δ Our method

5 DISCUSSION AND PERSPECTIVES

In the context of unfolding, the majority of methods proposed are sequential [8, 15, 16] with the insertion of *a priori* knowledge to sequence the segmentation. Several manual interventions are required to correct for some imperfections (holes, links between two lips of a sulcus or GM and ventricle horns) [8, 10, 16, 17]. In our approach tissues are segmented concurrently: several situated cooperative agents works in different parts of the image to segment GM, WM and CSF. The objective of our approach is to solve the following three major points: 1) to position correctly the agents, 2) to define adequate constraints for region-growing and 3) to control the global process. Positions and constraints, roughly defined at initialisation, are gradually refined thanks to information continuously gained locally and globally. Information added all along the segmentation process is rapidly diffused thanks to reactive agents behaviours. Qualitative maps are introduced to gather intermediate results and control agents behaviours. Then, augmentative (parallel region growing processes), confrontational (combination of information from agents working on different tissues) and integrative (interleaving estimation with data analysis) cooperation are processed in a coordinate way. For unfolding, a hard segmentation is required. A specific qualitative map, that contains for each voxel the degree of membership to a tissue, is inserted to take into account of partial volume effect, modelled as a gaussian mixture. This fuzzy map helps to improve the final labelling for hard MRI brain scans segmentation.

Our approach is in the same vein that this presented in [10] and applied to macaques brains segmentation, where local EM are used to deal with non uniformity of grey levels. EM is very sensitive to initialisation. We use peak finding on the overall image for EM initialisation. This can be improved in using prior classification based on a digital atlas. Spatial relations are elegantly modelled via MRF approaches. However, the Ising model, generally used with MRF approaches, leads to the blurring of fine structures incompatible with unfolding. Models preserving fine structures are computationally inefficient [21]. EM algorithm to estimate normal distribution presupposes grey levels as independent variables and no spatial relations are available. Here, spatial relations are introduced via agent's neighbourhood and are used to refine EM parameters obtained locally to its territory. Our results are then similar to those

obtained with MRF techniques with a lower computational burden (less than 5 min to segment a complete volume).

The technique proposed has now to be evaluated on real MRI brain scans. For this purpose, several improvements have to be introduced. Shading effect can appear inside agents territories. A bias field estimation map obtained following the technique proposed in [24] could be added to our model. Presently, interpolation is iterated until stabilization of all agents present into the system. Based on topological relations, agents could be gathered in groups and stabilization restricted to each group. Sulci maps obtained thanks to morphological operators or genetic approach could be added to help the GM ribbon detection. Tissues interfaces are prone to errors due to partial volume effect. In MRF model a specific term can be added to the energy function to provide information about local grey level variations [18]. Here, specific agents, working with confrontation and negotiation, and launched at tissues interfaces, could improve their detection. Introduction of anatomical information and the segmentation of sub-cortical structures could ameliorate the complete process of GM ribbon unfolding;

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