A Multi-Agent Approach for Self-adaptive MRI Segmentation

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***Abstract*—Medical image processing provides an important help for establishing diagnoses for several pathologies. In medical imagery, image segmentation is crucial for several applications such as lesion detection and delimitation, and tracking of disease evolution. Different image segmentation approaches have been proposed. However, the segmentation parameters are beforehand adjusted in most of those approaches. The latter do not allow the segmentation process to handle all the situations that can be found in the images. The goal of this paper is to introduce a new multi-agent approach for self-adaptive segmentation of Magnetic Resonance Image (MRI) data. Our approach is based on situated agents that interact together, and where each agent can perform discontinuity detection or similarity detection. Each agent parameters rely on its location in the image. That approach was implemented and tested on MRI data, and the first results are promising.**

Keywords–Image processing, image segmentation, multi-agent systems, Self-adaptation.

I. INTRODUCTION

In the last decades, medical image processing was one of the most active research fields in computer science. Segmentation is the most important and critical stage of the image processing. The high diversity of images and the inhomogeneity of artefacts' distribution within the images, such as noise and Intensity Non-Uniformity (INU) in Magnetic Resonance Image (MRI), require the segmentation process to be adaptive so that it can handle both the expected situations and unexpected ones.

Segmentation consists in partitioning a digital image into a set of separated regions, and it is mainly used to extract objects of interest present in an image. Several image segmentation methods were published in the literature. Those segmentation methods are mainly classified as follows [1]:

- Edge-based segmentation: Edge-based methods aim to find the places of rapid transition from one to other regions of different brightness or color value [2]. The edge is determined by the extreme of the first order derivative or a zero crossing in the second order derivative of the pixels' intensity function [3]. One of the first and most efficient techniques, in this approach, is the Canny edge detection algorithm [4].
- Region-based segmentation: Region based segmentation methods use a set of predefined criteria [3] to decompose an image into regions that contain connected pixels with similar properties. Most of the existing solutions use spatial information (pixel positions) with brightness information in the classification process of pixels. One of the most effective techniques is the region growing algorithm [5].
- Other techniques: Some of the segmentation methods described in the literature cannot be classified in the two previous categories. Most of them were borrowed from other disciplines and applied to image segmentation problem (genetic algorithm [6], graph theory [7], neural networks [8], etc.), or multi-agent systems (ant colonies, particle swarm optimization).

Multi-agent systems offer a set of properties that allow making image segmentation adaptive. They take into account several unexpected situations within the same image, or for a set of images. In recent years, many works have been published on image segmentation using multi-agent systems (for further details see [9]). Even if they are able to successfully achieve the image segmentation task, most of those multi-agent approaches are based on centralized agents and do not exploit the full advantages of multi-agent systems such as coordination mechanisms.

This paper introduce a new multi-agent approach for image segmentation and its application to MRI data. The system built with that approach is composed of two types of agents: Discontinuity agents and Similarity agents. Discontinuity agents use image gradient for boundaries detection. Similarity agents generate then homogeneous regions in an iterative and adaptive aggregation process. This process uses the results provided by the discontinuity agents that work on gray level intensity of pixels. Each agent self-adapts to the image data by tuning the best parameters according to the part of the image where it is located.

The paper is organized as follows. Section 2 describes and analyses existing multi-agent image segmentation approaches to show that the adaptation in such approaches is an open issue. Section 3 introduces the proposed multi-agent approach and we show how agents self-adapt according to the content of the image where they are located. Section 4 presents the implementation and the experimental results. Finally, Section 5 summarizes the contribution and describes some perspectives of this work.

II. RELATED WORK

Image segmentation is a very active field of computer science. Several approaches have thus been proposed (see [10]). To improve the efficiency of those segmentation approaches and to explore new ideas, recent works have proposed to use multi-agent systems to distribute the segmentation process, allowing adaptive processing in several cases. This section describes and analyses those multi-agent segmentation approaches.

Liu and Tang [11] introduced the first adaptive approach for image segmentation. They developed a multi-agent system based on a set of reactive agents operating in a 2D image. Agents select their behavior (breeding, moving and vanishing) according to local stimuli of the environment. Each agent explores the environment searching for a pixel of a homogeneous segment. After detecting this pixel, the agent breeds offspring agents in their neighborhood aiming to find the rest of the segment. Such behaviors is a kind of adaptation to the image content.

For the approach presented by Duchesnay *et al.* [12], the segmentation is performed in two steps:

- a pre-segmentation (using a quadtree for region detection and an edge detection algorithm for contour detection),
- and a merging process (using agents interaction).

In the first step, the system generates a set of regions and contours. They are then used to create a society of agents that are organized as an irregular pyramid and interact to make merging decisions. This process is repeated until the stabilization of the system. Agent self-organization, throw the merge process, can be considered as a self-adaptation of the organization according to the extracted segments of the image.

In [13], Germond *et al.* presented a framework for MRI image segmentation based on the cooperation of three different modules (a multi-agent system, a deformable model and an edge detector). The multi-agent system is composed of two different types of agents (region agents and edge agents). Those agents use information provided by the deformable model and the edge detector. Agents, in this system, adapt their processing according to the results provided by the previous modules.

The approach presented by Bourjot *et al.* [14] uses a swarm mechanism inspired by the collective web weaving behavior of social spiders for 2D grayscale image segmentation. The approach is modeled as a multi-agent system where reactive agents represent spiders exploring their environment, namely the input image. During this exploration and according to their behavior, agents interact together, select one of the three different actions (move, fix silk and return to web) to weave webs. Self-switching between behaviors according to the image data is also a kind of adaptation of agents to different situations.

Recently Arbai and Allioui [15] proposed a multi-agent system for the detection of Alzheimer lesions in MRI images. The system is divided into three main parts: the data, the knowledge, and the agents. In this configuration, three different sorts of agents (supervisor agent, analysis agent and segmentation agent) use the knowledge part to perform the segmentation of the MRI image according to the data part. This data represents the input image in addition to some information extracted with pre-treatment.This approach is based on the cooperation of agents using different segmentation methods.

Generally, MAS-based image segmentation relies on classical image segmentation algorithms. They encapsulate those algorithms in agents. They then endow those agents with interaction and coordination mechanisms to reach the global goal which is the partition of an image into its structural parts. However, in most of the published works, authors proceed by a fixed (off line) parameter tuning for all the parts of the image where agents process. So, agents perform segmentation task uniformly in the whole image. Such an approach does not allow processing images where artefacts are not uniformly distributed, such as MRI data.

In this work, we introduce a novel approach that allows agents to self-adapt to the image data, so the processing will be specific to each part of the image where an agent operates.

III. A NEW MAS APPROACH

In the proposed multi-agent based approach, segmentation is based on the collaboration of different types of agents. The latter are situated in an environment, which is a two dimension MRI image. Those agents interact to achieve the image segmentation. Two kinds of agents are used and are built aiming to get benefits on the discontinuity and the similarity properties of pixels. The discontinuity allows finding boundary pixels of regions, while the similarity allows the agglomeration of all pixels sharing a similar gray level intensity. The two populations of agents cooperate to accomplish their goal: partitioning the image into homogeneous regions. The segmentation process is described in Figure 1. The two main phases of the system are: discontinuities detection and similarities detection.

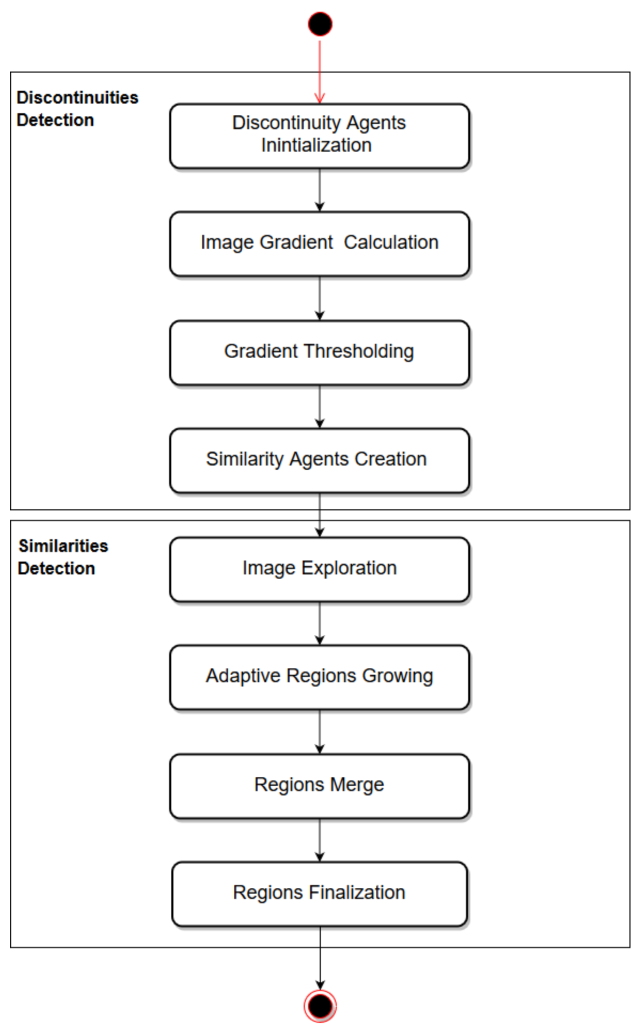


Figure 1. The two stages of image segmentation.

We show, in the following subsection, that similarity agents are self-adaptive and perform region growing according to the sub-region where they are situated. Each agent calculates the used parameters according to the artefacts in the part of the image where it operates, namely the noise and the Intensity Non-Uniformity (INU).

A. Discontinuity detection

Discontinuity agents (DAgents) are created and uniformly dispersed on the image. The image is decomposed in areas, where each one is associated with a DAgent. DAgents are thus situated; they execute their behavior without moving from their positions. They first calculate the standard-deviation of the image data at the pixels in their respective areas. If the calculated standard-deviation is bellow a given threshold, each agent labels all the pixels of its area as probably region pixels (Class 1). Otherwise, the agent estimates the gradient of the pixels included in its area using a Sobel Filter [16]. The gradient is then used to perform a *k*-mean clustering. Pixels with high gradient are labeled as boundary pixels (Class 2), pixels with low gradient are labeled as region pixels (Class 1). Finally, DAgent chooses in its area the pixel (labeled C1) with the lowest gradient and creates a Similarity Agent (SAgent) on that position, and provides it the pixel similarity threshold (PST) which is set to the standard-deviation of its area.

B. Similarities detection

SAgents are mobile agents exploring the image, seeking homogeneous regions to detect and to delimit. The agent behavior and parameters are defined so that the regions of the image can be extracted despite the alterations it contains, which are the INU and the noise. After their creation, the agents start their activity using the following behavior:

1) Exploration: A SAgent explores its environment searching for a seed pixel. A seed pixel is a Class 1 pixel with no Class 2 pixels in its neighborhood. The size of the neighborhood can be set manualy according to the content nature of the processed images. It is low (3 x 3) for images that contain a lot of details such as outdoor images, and it is higher for images with vast homogeneous regions such in several medical images. When encountering a seed pixel, the SAgent switches to the next behavior.
2) Region Growing: The method used in this step was partially inspired by the work of Pohle and Toennies [17]. Firstly, starting from its initial position, a SAgent uses a random walk to self-adapt to the homogeneous region in which it is moving, and estimates its features. During this walk, the SAgent considers all the encountered $Class1$ pixels with a similar gray level, up to the threshold PST. The latter depends on the SAgent, and it was communicated by the DAgent. Its value depends on the intensity of the pixels forming the neighborhood of the seed. Secondly, the SAgent uses the set of explored pixels to calculate the features of its region (i). The used features are the gray level mean E_i and the standard derivation σ_i. Finally, these features are used to perform a standard region growing. The SAgent, starting from its seed pixel, iteratively adds to its region, all the surrounding pixels satisfying the assimilation predicate P and then, updates its region.

$$P(Pixel) = \begin{cases} true & if\ I(P) \in [E_i \pm (\sigma_i \times \alpha)] \\ false & otherwise \end{cases}$$

where $I(P)$ is the intensity of the pixel P, and α is an adjustment parameter. This processing is iterated until no more adjacent pixels can be added. The result of this step is generally an over-segmented image with too many regions. This over-segmentation has to be refined using a merge operation.
3) Region Merge: In this step, The SAgents interact together to expand their regions by merging with those of their neighbors. Two SAgents are considered as neighbor if they have adjacent region borders. During their interaction, the SAgents use the contract net protocol [18] to evaluate the relevance of the merge of their two regions. Each SAgent evaluates the benefits of a merge by comparing the standard-derivation of its region before and after the merge. All possible merges are considered, and the SAgent selects the one that minimizes the resulting standard derivation. Then, the SAgent performs the merge of its region and the chosen one. Lastly, the agent that has performed the merge updates its list of neighbors and starts looking for another merge, while the other agent (involved in the merge) will be deactivated. The process is repeated wwhile a merge is possible between two neighbors.
4) Region Finalization: the purpose of this step is to calculate the final borders of the detected regions. It also allows the smoothing of the obtained regions. Each SAgent browses the pixels situated inside its region that were initially excluded during the region growing step. The SAgent then assimilates all the pixels that satisfy the assimilation condition according to the new region assimilation parameters.

When no more agents are active, the system stops and the set of the non-overlapping obtained regions are displayed. Similarity agents self-adapt to the levels of the artefacts in their respective sub-regions by calculating and using suitable parameters. In classical methods for MRI segmentation, a first stage for INU elimination must be performed, where it is not always successful and it is time-consuming because of its iterative nature

IV. Implementation and Experiments

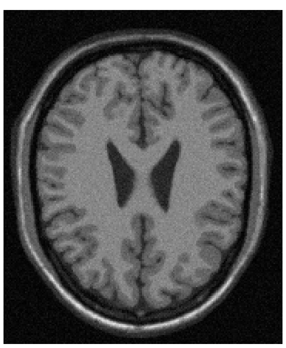
For the implementation of our approach, we choose to start from scratch instead of using an existing platform such as JADE or MADKIT. Our Multi-agent system is composed of reactive agents with simple behavior and very low communication. Thus, we use the $CSharp$ language and Microsoft .Net Framework to implement our agents as generic classes. We believe that this implementation allows us to keep full control of the system and allows optimizing its performance. C Sharp has already been used in multi-agent simulations [19] and it provides an efficient, reliable, and easy to program agent framework for the development agent-based applications [20].

To validate the efficiency of the implemented approach, some MR images from the Brain Web dataset are used.

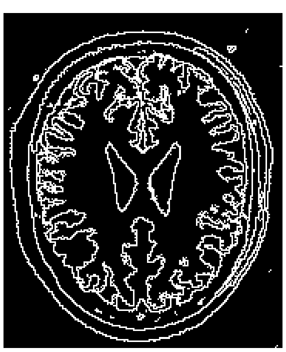
Experiments are performed on a PC with an I7 1.9 GHz processor and 8 GB RAM.

For our experiments, we choose the Brainweb phantom database that it is a MRI dataset produced by McConnell Brain Imaging Center at Montreal Neurological Institute [21]. It provides different simulated brain phantom volumes, with different simulation options among which values of noise and intensity non-uniformity. In our experiments, we use bi-dimensional slices extracted from T1 MRI with an image size 181x217, and a pixel size of 1mm x 1mm. Those images are generated in 9 versions by varying the level of noise (5%, 7%, 9%) the level of intensity non-uniformity (0%, 20%, 40%) called INU. The image shown in Figure 2a is a slice of an MRI. It is an image with a high level of noise. It is provided to the implemented multi-agent segmentation system as an input image. The system uses then the approach described in the previous section. First, we show, in Figure 2b, the different regions forming the brain tissues by averaging the intensities within the slice. Figure 2c represents a binary image of the contours that are generated at the first step of the segmentation process by the population of DAgents. Figure 2d introduces the region corresponding to the white matter tissue of the brain at this slice. We can notice that despite the high level on the artefacts, the region was well delimited.

Figure 3 and Figure 4 introduce the results with two MRI from the same dataset, with higher levels of INU (respectively 20% and 40%) and the high level of noise (5%). We can note that despite such high level of deformation (Figures 3a,4a), the obtained region contours, and the extracted white matter region, introduced respectively in Figures 3c, 4c and Figures 3d, 4d were correctly computed.


(a) MRI Slice


(b) Average Gray Level


(c) Detected Edges

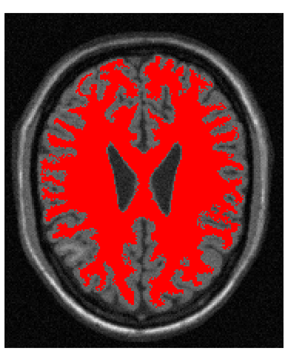
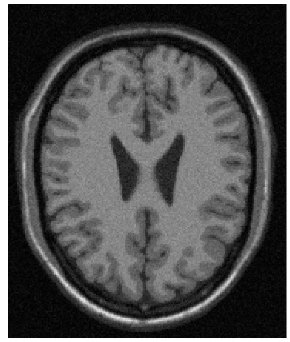
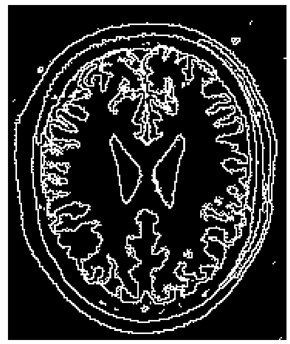

(d) WM Region

Figure 2. Segmentation example of a MRI slice with 5% of noise level and 0% INU.


(a) MRI Slice


(b) Average Gray Level


(c) Detected Edges

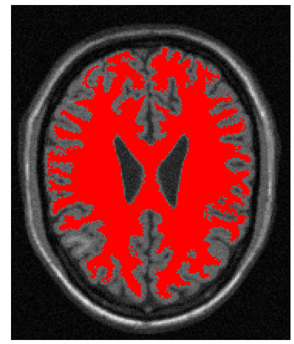
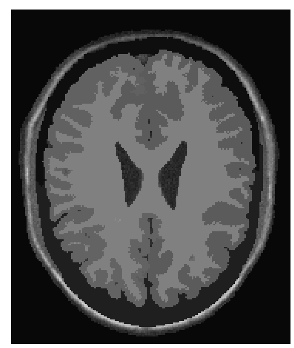
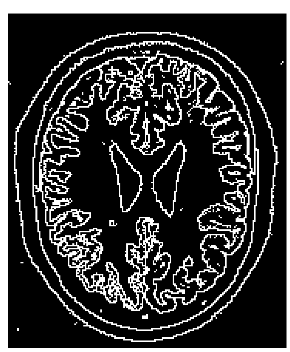

(d) WM Region

Figure 3. Segmentation example of a MRI slice with 5% of noise level and 20% INU.


(a) MRI Slice


(b) Average Gray Level


(c) Detected Edges

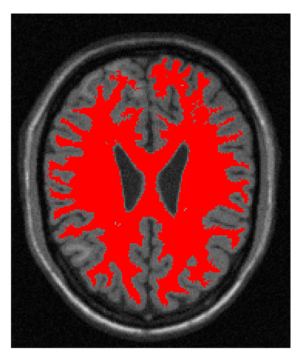

(d) WM Region

Figure 4. Segmentation example of a MRI slice with 5% of noise level and 40% INU.

According to the visual results, we can note the potential of our approach to segment MRI data, by considering the whole volume, slice per slice. In particular, we have faced the INU problem in MRI by making agents self-adapt to their respective sub-regions, so the artefact was efficiently treated. To quantitatively evaluate our approach, we conducted a set of tests using the κ-coefficient (kappa), also known as Dice similarity coefficient as the evaluation metric for the White Matter region extraction. This coefficient is commonly used in the medical image processing to evaluate the performance of segmentation algorithms which has a predefined ground truth information or dataset. It is calculated using the following formula [22]:

$$\kappa = \frac{2 * TP}{(2 * TP) + FP + FN} \tag{1}$$

where TP, FP and FN are the numbers respectively of True Positive, False Positive and False Negative instances of pixel labeling. The value of the κ coefficient well expresses the segmentation quality.

The results of our experiments are presented in Table I:

TABLE I. κ Coefficient calculated for white matter extraction with different noise and INU levels

	INU levels		
Noise levels	0%	20%	40%
κ for 5%	93,4	94,9	94,7
κ for 7%	91,5	90,4	92,0
κ for 9%	91,2	89,5	90,5,

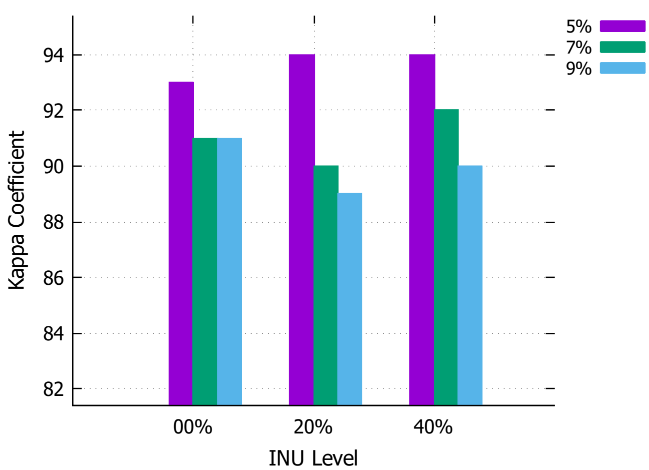


Figure 5. κ coefficient evolution for White Matter extraction with different noise and INU levels

Table I and Figure 5 show the effectiveness of our approach for the White Mater despite the increase in artefact levels occurring in the processed image. The obtained results show that the increase in noise level has an impact on the quality of the extraction, which is acceptable at such levels (5%, 7% and 9%). This incidence is still minor compared to the level of image degradation. Figure 5 also illustrates the robustness of the approach against the INU artefact of the segmented image. It thus reflects the adaptation that our system can demonstrate in the execution of its task.

In addition to the intrinsic evaluation, we evaluate the quality of our results by comparing them to the ones obtained from other segmentation methods published in the literature. For this purpose, we used the comparison data provided by Yazdani et al. [23]. The results introduced in [23] concern volumic data, while ours are obtained from 2D slices. Nevertheless, this does not significantly affect the κ coefficient in our case because it is based on ratios of large sets of pixels or voxels.

TABLE II. κ Coefficient calculated for white matter extraction with different noise levels and 20% INU level

	Noise level		
Approches	5%	7%	9%
Our System	92,0	94,0	93,0
EM	92,2	90,1	86,4
SPM 5	93,6	90,2	86,3
HMC	93,9	92,3	91,7
Fast	94,8	94,3	91,9
FCM	92,0	88,0	84,0
NL-FCM	91,5	89,8	83,2
UFBSMRI	94,9	94,4	92,2

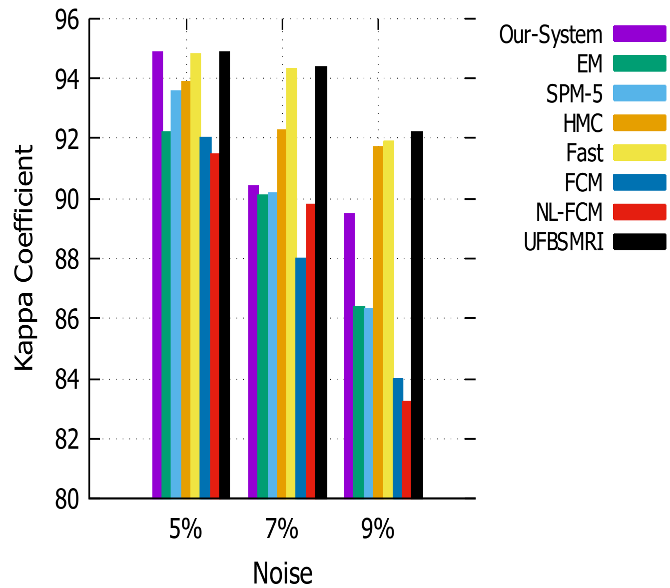


Figure 6. κ coefficient evolution for White Matter extraction with different noise levels and 20% INU level with different approaches

In Table II and Figure 6, we can note that our multi-agent system has acceptable results and has a good robustness against increasing noise, compared to the methods involved in the comparison. Due to the absence of data concerning the other approaches for various INU levels, we were only able to compare our results according to only 20% INU level.

With these results, we can assume that due to their capability of self-adaptation to their respective regions, the agents of our approach do not need training data. Such a feature allows the method to be usable for different images with several artefact levels, without previous training. Also, agents are weakly coupled, so they permit the physical distribution of the method.

V. Conclusion and Future Works

In this paper, we proposed a new multi-agent approach for MRI segmentation. That approach is based on two different populations of agents: Discontinuity Agents (DAgents) and Similarity Agents (SAgents). These different agents interact in an environment, namely the image, to perform its segmentation. DAgents use image gradient and k-means classification to distinguish boundary pixels from region ones. SAgents use then the resulting classification during the region detection process. SAgents start with an adaptive region growing algorithm, where agents are competing to expand their regions. When no more expansion is possible, SAgents collaborate the merge their regions.

The proposed multi-agent approach does not require any human interaction during the image segmentation. It also self-adapts to different levels of image artefacts. Other advantages of our approach are its capability of detecting many regions in parallel during the segmentation process and its robustness to noise and INU. Our approach gives promising issues for the segmentation of different kinds of images. However, this approach still suffers from some limitations such as the setting of some parameters. Moreover, Other self-adaptive agent strategies, such as social utility, will be considered in future works.

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