A Generic Multi-Agent Framework for Medical-Image Segmentation*

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Abstract. Medical images offer visual representations of human bodies' complex internal structures. One of the most common process applied to those images is segmentation. It consists in dividing an image into a set of regions of interest. Human anatomical complexity and medical image acquisition methods make the segmentation of medical images very complex. Several solutions (algorithms and devices) have thus been proposed to automatize this process. However, most existing solutions were developed for one type of images and/or require several inputs of the user. In this demo, we propose a generic multi-agent framework for medical image segmentation. This framework is based on a set of autonomous and interactive agents that use a modified region growing algorithm and cooperate to segment the images. Experiments were performed on brain MRI simulated images and the obtained results are promising.

Keywords: Medical Images, Segmentation, Multi-Agent Framework, Interaction, Region Growing Algorithm.

1 Introduction

Medical imaging requires several complex tasks such as segmentation. Image segmentation is a key technique in providing non-invasive information about human body structures. Lately, it became an essential tool used in medicines to collect information about patient's health condition in a non-invasive manner.

The image segmentation research community has developed several algorithms and tools. They are often based on thresholding [24], region growing [1, 14], and methods borrowed from other disciplines like Markov Random Fields [13] and Deformable Models [16]. Most existing segmentation techniques are ad hoc. They are specific to the type of images that were designed for. Meanwhile, new medical tools, e.g. PET-SCAN, generate several types of images. In this context, we propose a generic framework for medical image segmentation.

* https://youtu.be/oCVLA81gI3c

This framework is designed as a system composed of two different types of autonomous agents, which interact and coordinate in an environment (the treated image) to perform the segmentation process. Firstly, the first set of agents start classification process based on pixels gradient level and use this classification to initiate the second set of agents. These latter starts then exploring the image to identify the regions, they perform region growing process and explore the possible merging between regions. Finally, they remove noise to improve the quality of the regions.

The aim of this demo is to describe the proposed framework and illustrate the behavior of the implemented multi-agent system on medical images. It is organized as follows. Section 2 describes the context and related work. Section 3 describes the framework and Section 4 gives some details about its implementation.

2 Related Work

The automation of the medical image segmentation is a very challenging problem due to the nature of images acquisition methods and artifacts. Many research projects were published in this field. The following section gives an overview of medical image segmentation issues and presents the related work.

2.1 Medical Image Segmentation

Medical image segmentation is a key technique in providing non-invasive information about human body structures. It helps radiologists to visualize and study the anatomy of those structures. The so obtained information is used for different purposes like pathologies diagnostic, pre-operative planning and image guided surgical Procedures, diseases progress tracking and treatment planning [11].

An accurate segmentation is vital in medical imaging, but it is difficult to obtain, and therefore remains an open issue. The difficulty of segmenting those images comes from different factors including their methods of acquisition and sampling (CT Scans and magnetic resonance for example) that generate noise (acquisition) and partial volume effect (sampling), the complexity of human anatomical structures, the tissues intensity non-homogeneity, the closeness in gray level of different soft tissues (low contrast) [22] .

A wide range of medical image segmentation approaches were introduced for segmenting different modalities and pathologies. Those approaches use different techniques such as threshold [24] , region growing [1, 14] , Markov Random Fields [13], Fuzzy and Hard Clustering [2, 10], and Deformable Models [16]. They are often coupled with preprocessing techniques to reduce noise or artefacts, or with manual initialization [6]. All those approaches employ a monolithic, sequential and centralized systems to perform complex tasks [3]. To improve segmentation system efficiency, some approaches explore the usage of systems based on cooperative problem resolution called Muli-Agent Systems.

2.2 Multi-agent Segmentation Approaches

Recently, significant applications in different fields of the health care domain were developed using the multi-agent paradigm [5]. Among those applications, is the medical image segmentation. Several multi-agent approaches have been proposed to deal with medical image segmentation. We distinguish two categories. In the first category, the agents encapsulate one of the various existing methods and try to improve it using different mechanisms (distribution, information diffusion. . .). The second category, on the other hand, attempt to exploit the potential of multi-agent systems by using the tools that they provide like coordination and cooperation. In this category we can find solutions that rely on social coordination mechanisms such as ant colonies and social spider colonies [17]. For instance, Djemame et al. [9] use self-organization and adaptation of social spider in a MAS to extract homogeneous regions of an image. Liu and al.[15] use agents with living beings behavior to extract brain structures in a scan image. Richard et al. [21] use cooperative and interactive behaviors to respectively distribute the work and propagate information among agents of their MAS to segment medical images.

According to the literature, region growing method (RGM) is well suited for multi-agent medical image segmentation systems in both previously mentioned categories. Some systems use RGM on images sub parts, to label pixels from a set of known classes like [20] with MR brain images or [7] working on CT image scans. Other MAS approaches associate RGM with other segmentation methods, such as [12] with Fuzzy C-Mean method on brain MR images, [3] with Region Fusions on the same type of image, and also with Region Fusion in the process of microaneurysm detection in fundus images by [18].

2.3 Discussion

The previous sections describe interesting and innovative approaches. Most of those approaches provide promising results. However, they often suffer of one or several drawbacks [4]:

- Each approach is specific to the type of images that was designed for and does not support generalization;
- Each approach is based on a prior knowledge or a training data set that affects the segmentation results;
- Each approach requires a user intervention for setting up parameters or thresholds.

In the aim of overcoming some of these disadvantages, we developed the adaptive multi-agent approach for medical image segmentation. The proposed approach was implemented in a Multi-agent dedicated framework. The latter is described in the following section.

3 MAMES: A Multi-Agent framework For Medical image Segmentation

MAMES relies on an evolution of the multi-agent approach presented in [4]. The system uses two populations of agents to perform segmentation of medical images. The different agents are situated in an environment that is defined as a two-dimensional matrix of pixels. Each pixel contains two types of information: the scalar gray level intensity of the corresponding pixel in the processed image, and a vector value of the gradient on this pixel. This gradient value is obtained by the application of a Sobel filter on the initial image.

The image segmentation is performed in two steps: 1) classification of pixels and 2) region detection. These two steps are realized by two different populations of interactive and situated agents and are described in the following sections.

3.1 Classification of pixels

The first population of agents aim is classifying image pixels into two categories according to their gradient level: class 1 (C1) with height gradient values (edge pixels and neighborhood) and class 2 (C2) with low gradient values (region pixels).

The agents of this population (named Thresholding Agents) use this classification to choose the seed pixels where to create the entities of the second population of agents (named Region Growing Agents).

The thresholding agents are dispersed homogeneously in the environment, where each agent is assigned to a subpart of the image. Then, the agents are launched to perform the following steps:

1. Thresholding Behavior: After its activation, a Thresholding Agent (TAgent) analyzes its assigned area by comparing the gray level (GL) of its pixels. If all pixels have the same GL, the whole area is classified as C2 pixels. Otherwise, the TAgent uses a classic K-means clustering algorithm to perform the classification of pixels area according to their gradient value. Then, the agent labels those pixels according to the resulting classification.
2. Adjacency Graph Creation: TAgents interact together and generate Adjacency Graphs where agents are the vertices. In those graphs, two vertices are adjacent if there is a discontinuous linear sequence of C2 pixels connecting them in the image. At the end of this process, each subset of connected TAgents creates a Region Growing Agent (RGAgent). This RGAgent is initialized in the position (pixel) of the TAgent in the graph, having the highest number of connected neighbors.

3.2 Region Detection

The goal of the region agents is to detect the regions composing the image. Those agents (RGAgent), similarly to [4] use a modified version of the growing approach proposed in [19]. A RGAgent starts growing its region from its seed pixel (previously set by the TAgent). When the region becomes sufficiently large, the agent explores possible merging with its neighbors. Lastly, RGAgents starts to finalize their regions by using the GL and the position of pixels for noise removing process.

1. Initial Region Growing: This first phase is used to determine the characteristics of the region. Starting from the seed pixel, the agent uses a random walk and adds to its initial region R_{init} any pixel P classified in $C2$ and with a gray level similar to the gray level of the growing region.
2. Final Region Growing: In this phase, the agent exploits the information collected during the previous phase. It calculates the mean gray level $E_{R_{init}}(G)$ and standard derivation $\sigma(R_{init})$ of the pixels of the initial region. Those two values are then used to evaluate the predicate of pixel assimilation during this region growing phase.
   Starting from the seed pixel, the agent creates its final region, and its neighbors' pixels are considered as the contours of this region. Thus, at each step of execution, the agent browses the list of its contour pixels, assimilates all of those pixels that satisfy its predicate, and updates then its contours. This growing process is repeated while some contour pixels satisfies the agent predicate.
3. Merging: In this step, RGAgents use region neighborhood concept, where two regions are considered as neighbor if they have borders in common. Thus, The RGAgents attempt to expand their regions by merging with their neighbors. They use the contract net protocol [23] to evaluate the relevance of a merge by comparing the standard derivation before and after a possible merge. This evaluation is then used to choose the best merging among the list of neighbors. According to this selection, RGAgents perform merging, update their neighborhood and restart searching for another merge. The process is repeated until no merge possibility is detected within neighbors list.
4. Region Finalization: Each RGAgent tries to assimilate all the pixels that actually belong to its region, but are affected by a noise effect due to the acquisition method. RGAgent browses the unassimilated situated inside his region and assimilates all the ones that satisfy a predicate where the GL of the pixel and its position in the region are considered.

When an agent cannot add anymore pixels to its region, it marks the bordering pixels as contours and self-deactivates. The whole system stops when all agents are deactivated.

4 Implementation and Experiments

4.1 Implementation

The Multi-agent framework MAMES consists of a population of reactive and situated agents with simple behavior and limited communication. Moreover, the segmentation process is time-consuming the reason why we implemented MAMES with C# and MS.Net framework instead of using available multi-agent tool such as JADE or MADKIT. Our implementation allows us to maintain total control of the system and fully optimize its performances. Our agents are implemented as simple C# objects concurrently executed under the control of a scheduler.

To exploit MAMES, We also develop a desktop application with a simple and functional interface (see Fig. 1). The Application can process the standard 2D image formats and can also extract 2D slices from image volumes. The tool was designed with the C# Winform technology and offers the following features:

– Opening and viewing digital 2D images to process.
– Opening digital 3D Volumes and extract a 2D slice for segmentation.
– Segmenting an image with the proposed multi-agent approach.
– Viewing the classification resulting from the distributed Thresholding first step.
– Viewing the resulting regions detected by the system on the initial image.
– Viewing the characteristics of the resulting regions (size, average gray level, standard derivation).
– Viewing the detected contours.

The Fig. 1 represents the main interface of our prototype tool that we use to perform our experimentation. The obtained results are presented further in this section.

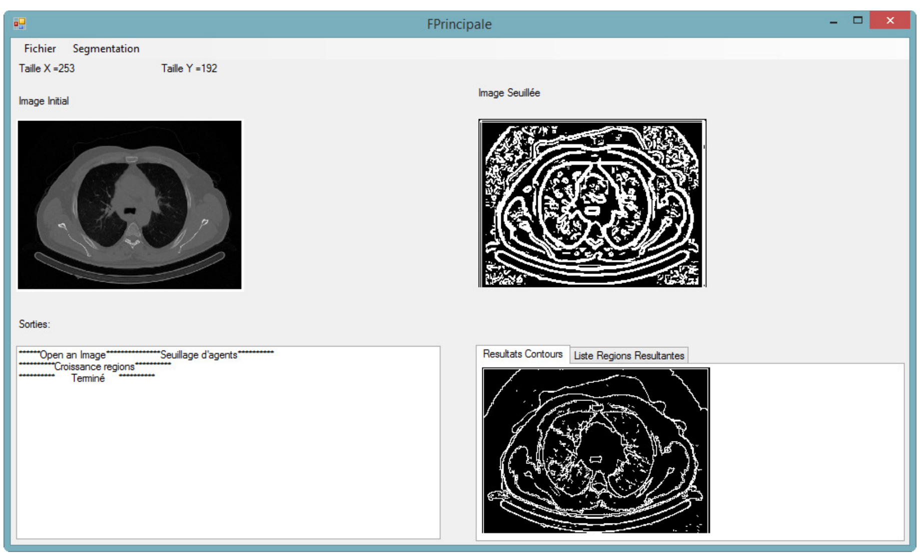


Fig. 1: Application main form

4.2 Experimental Results

In order to verify the efficiency of our multi-agent image segmentation framework and to insure his robustness, we perform some experiments with different sorts of medical images.

The first set of our experiments were performed on a brain MRI phantom image simulated using the phantom database produced by McConnell Brain Imaging Center at Montreal Neurological Institute [8]. Using this simulated images permits the verification of the efficiency of our approach, despite the variation of image artifacts such as noise and intensity non uniformity (INU) in a quantitative evaluation. For this evaluation, the system is tested for the detection of white mater region on eighteen versions of a brain MRI slice (six different noise levels and three different INU levels). The used evaluation metric is the κ-coefficient (kappa), also known as Dice similarity coefficient [25]. 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 [4]:

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

where TP, FP and FN are the numbers respectively of True Positives, False Positives and False Negatives instances of pixel labeling. The value of the κ coefficient well expresses the segmentation quality.
The results of our experiments are presented bellow:

	White matter					
Noise level	0%	1%	3%	5%	7%	9%
κ for 0% INU	90	91	93	95	94	91
κ for 20% INU	92	91	94	95	93	87
κ for 40% INU	89	91	91	89	86	85

Table 1: κ coefficient for White Matter extraction with different noise and INU levels

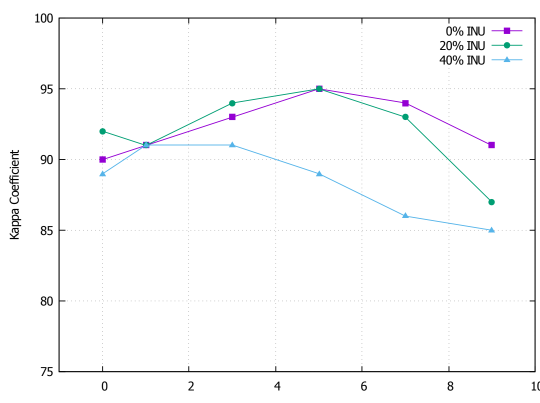
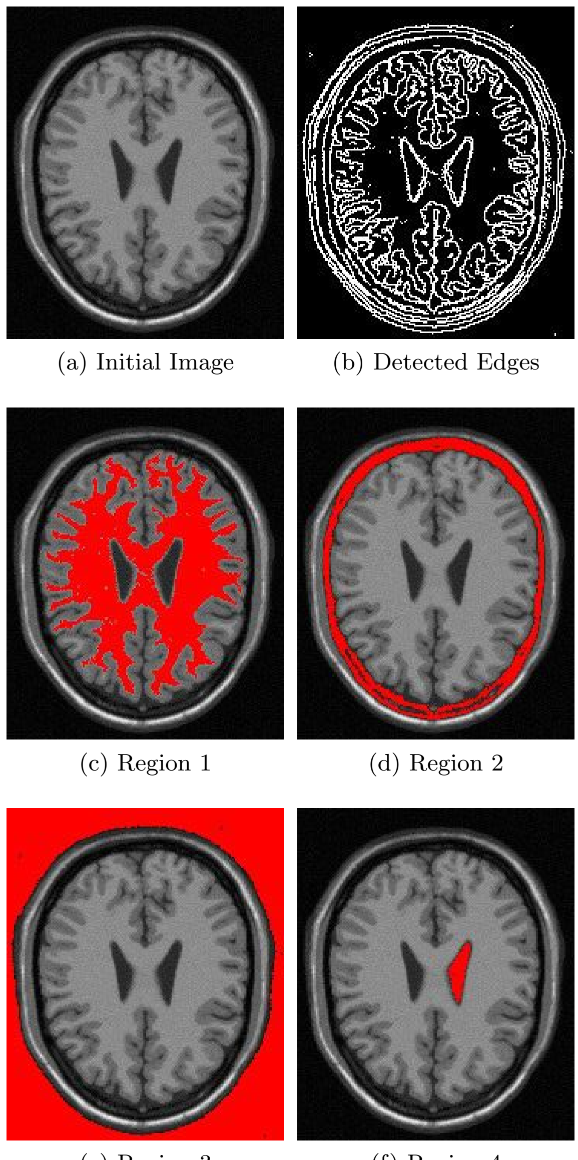


Fig. 2: Application main form

Table 1 and Fig.2 demonstrate the effectiveness of our system even with the increase of noise level and INU level. Those results are very promising considering that the system doesn't need any learning dataset or pre-treatment, and the unique experimentally defined parameter is the agents population initial size.



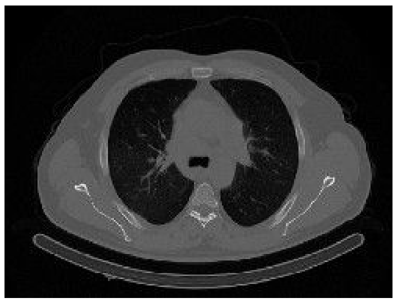
(a) Initial Image (b) Detected Edges

(c) Region 1 (d) Region 2

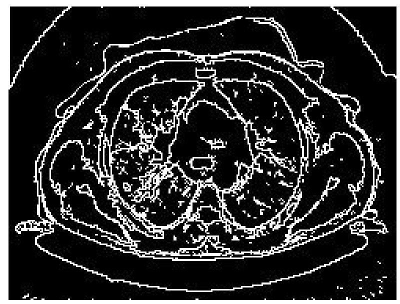
(e) Region 3 (f) Region 4

Fig. 3: Segmentation example of a brain slice with 20% INU level and 3% of noise

Finally, to verify the capacity of our system in segmenting different sorts of medical images, we tested it on a computerized tomography image of a human abdomen and on a cranial scan in addition to the MRI brain images. Fig.4 and Fig.5 allow a visual evaluation of the results. We can note that even with different kinds of images, our system was able to extract regions with efficiency.

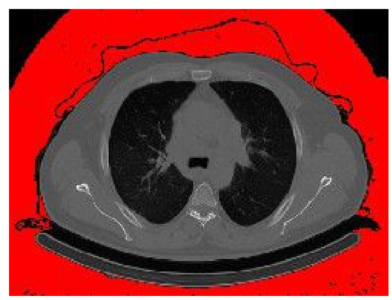


(a) Initial Image



(b) Detected Edges

(c) Region 1

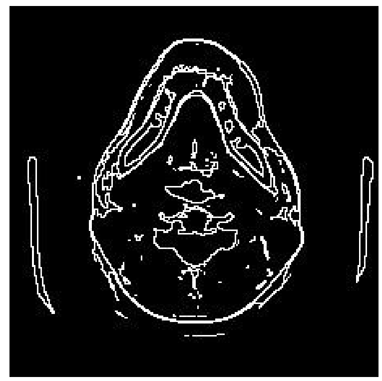


(d) Region 2

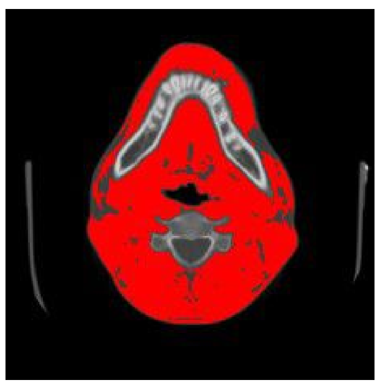
(e) Region 3

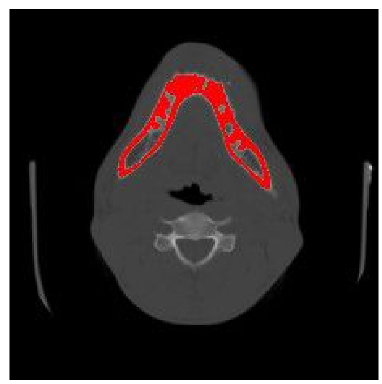
(f) Region 4

Fig. 4: Segmentation example of a computerized tomography image of a human abdomen

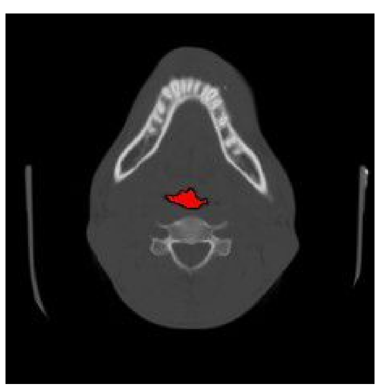


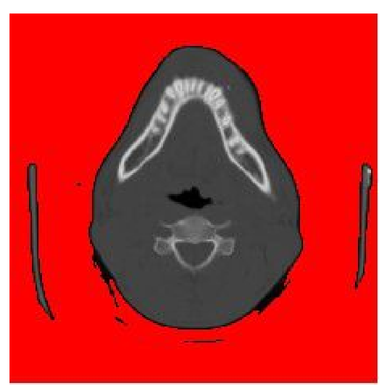
(a) Initial Image (b) Detected Edges





(c) Region 1 (d) Region 2





(e) Region 3 (f) Region 4

Fig. 5: Segmentation example of a human cranial scan

5 Conclusion

In this paper, we presented a multi-agent framework for medical image segmentation (named MAMES). MAMES implemented multi-agent systems that allow the simultaneous detection of different regions without any input of the user related to the image sort such as the region number, thresholds or some characteristics pre-defined with a learning phase or a prior knowledge.

MAMES relies on two populations of interactive agents (Thresholding Agents and Region Growing Agents) for image segmentation. The first population, named Thresholding Agents, classify the pixels and interact together to chose the best initial positions of the second population agents', named Region Growing Agents. The latter create then new regions and start the growing process. When the evolution of the region becomes not possible, the agents start a coordination process to perform the best merging. This process is repeated until no more possible merge were found. The agents then finalize their regions with a noise removing step.

MAMES was used to segment several medical images. The performed segmentation experiments validated its implementation and targets characteristics performance such as the genericity of MAMES and the segmentation quality.

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