

An Improved Image Segmentation System: A Cooperative Multi-agent Strategy for 2D/3D Medical Images

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Abstract—In this paper, we present a solution-based cooperation approach for strengthening the image segmentation. This paper proposes a cooperative method relying on Multi-Agent System. The main contribution of this work is to highlight the importance of cooperation between the contour and region growing based on Multi-Agent System (MAS). Consequently, agents' interactions form the main part of the whole process for image segmentation. Similar works were proposed to evaluate the effectiveness of the proposed solution. The main difference is that our Multi-Agent System can perform the segmentation process ensuring efficiency. Our results show that the performance indices in the system were higher. Furthermore, the integration of the cooperation paradigm allows to speed up the segmentation process. Besides, the tests reveal the robustness of our method by proving competitive results. Our proposal achieved an accuracy of $93,51\% \pm 0,8$, a sensitivity of $93,53\% \pm 5,08$ and a specificity rate of $92,64\% \pm 4,01$.

Index Terms—2D/3D image segmentation, Multi-Agent System (MAS), Medical images, Multi-Agent System Cooperation, Improved cooperation.

I. INTRODUCTION

Nowadays, all imaging systems are designed to ensure sustainability and build prosperity to develop a powerful treatment strategy. Segmentation is one of the keystones of medical diagnosis [1]. The segmentation consists of splitting an image into subparts according to one or more criteria. The obtained subparts, called segments, must be distinct and homogeneous. Thus, good segmentation needs to be specific, relevant, measurable, accessible, and time-bound. Image segmentation has a crucial role, particularly in medical imaging. Its results can be used either in the quantitative analysis [2], object detection [3], diagnosis [4], disease detection [5], or even surgery planning [6]. Yet the average time required for a

specialist to perform manual segmentation reach three hours given the amount of data processed. These challenges reveal the huge need for a fast and reliable method. However, the segmentation faces other challenges because of the varied content of images, the collected objects, image noise, etc.

One of the issues that keep bothering researchers is the way to segment and analyze the image correctly. There was a time when image segmentation required simple criteria to segment an image. Recently, the increasing need to have granular information, and to study the actual complex phenomenon and disease require more developed methods. So far, a lot of effort has gone into researching approaches based on Sobel operator [7], the Laplacian operator [8], the Canny filter [9], clusters [10], graph cuts [11], the random walker [12], Thresholding [13], Markov Random Fields [14], active contour models [15], level sets [16], and mean-shift [17]. Despite methods diversity, edge detection [18] and regions [19, 20], have always been either subject of segmentation researches. Although each approach has its advantages, it also has drawbacks. This led to the focus on cooperative approaches to improve methods strengths and efficiency.

Evidence suggests that other aspects need to be used to enable more meaningful image segmentation such as cooperation or the use of intelligent environments. Thus, the agent paradigm [21] incorporates qualitative constraints of cooperation. For that, vision systems use the functionalities of MAS such as interactions, individual or social behavior in a decentralized way to share the agents' knowledge.

The main contribution of our paper is an improved segmentation system based on strong cooperation techniques. Our automatic system deploys a MAS to strengthen the image segmentation process from several points:

- We intend to provide a strong assistance tool for clinicians, not to replace their works.
- The MAS adopted allows the identification of areas of interest in the studied images and conflict resolution during the cooperation of both methods (contour/region).
- Our collaborative MAS offers a solid base of agents' behavior management.

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- Our approach was tested on public data sets and proved high-efficiency rates with a competitive accuracy comparing to state-of-the-art methods.

The rest of this paper is organized as follows: Section II provides an overview of the related works. In section III, we explain our cooperative approach. Section IV details the resolution process. Section V describes the experimental results and the conclusion in section VI.

II. RELATED WORKS

Many studies have been conducted to analyze images and ensure segmentation tasks. Researchers have shown that segmentation-based strategies receive higher interests. Segmentation is defined as partitioning images into different significant regions [22]. Segmentation can be applied in medical imaging to perform various tasks (tumor localization, pathological tests, my measurements of tissue volumes, diagnosis, computer-assisted surgery, and cure planning). In the literature, several works proved accurate results.

However, contour-based techniques depend on the information contained in the local areas of the image, which leads to several limitations. It signals more difficulties because of its sensitivity to noise. Whereas, region-based techniques study local or global information to group pixels that have common properties. Yet, segmentation using region methods remains limited in different situations, such as the difficulty of identifying the criteria for seed progression or the non-correspondence of the obtained regions to real objects in the image, this is because the edges of the obtained regions are generally inexact and don't exactly match with the edges of the objects in the image.

In medical imaging, traditional methods and manual creation time of static segments are barriers to having timely, relevant information for decision-making. Edge detection ensures an evaluation measurement process using double evaluation criteria [23]. Yet, region growth also asserts important difficulties in terms of automatic seed generation and pixel sorting orders [24].

Both approaches edge and region offer a multitude of methods aiming to perform the segmentation of some image types, which limits their application fields. Indeed, to face sensitive segmentation problems, it is required to adjust a performant method that overcomes methods' drawback by using the cooperation paradigm of the two methods (edge and region) also by strengthening it by the functionalities of the MAS.

For years, MAS was used in solving computer vision complexities. Several research studies have been based on the principles of parallel processing distribution with good solutions for image segmentation. The authors in [25] presented a reactive MAS for brain MRI segmentation. The use of agents' environment proved efficient results compared to the classical algorithms. Richard and al. [26] introduced a hierarchical cooperative system to segment MRI brain images. They used

three types of agents, with three control levels. However, the interactions between the agents can impact the necessary parameters for the segmentation's achievement. Later, [27] proposed a microaneurysm method based on MAS for image segmentation. They achieved competitive results. The authors in [28] proposed a multi-agent approach to apply region growing algorithm.

In image processing, using MAS ensure self-organization for task accomplishments. An agent has the ability to move autonomously according to environmental conditions. The principle of MAS is to study the whole system, taking into consideration the collective behavior and the information transmission between the different autonomous agents. The agent [29] must perceive his environment, communicate with others, and negotiate with others in conflict situations to achieve his goals in the system. Indeed, the interactions between several agents make it possible to complete a task such as an image segmentation [30].

III. THE PROPOSED SYSTEM

Being an autonomous entity, the agent may lack expertise in some image segmentation tasks. The agent is facing more constraining procedures in 3D and may have low motivation as well as reduced reactivity. Consequently, an error in the agent's tasks can have consequences in terms of quality. In contrast to the case of using a single agent responsible for taking all decisions, the use of multi-agent systems consists of increasing operational efficiency by distributing responsibilities and tasks during the segmentation process. Adopting a MAS in the segmentation process is to take advantage of the possibilities of delegating the authority to agents at lower levels of responsibility. Each agent can decide on local matters, but it decides locally, through its interactions not in a global way. In image segmentation, MAS is a promising alternative to decentralize computations. For that, our approach benefits from the advantages of MAS use and points to the cooperation of three principles: contour segmentation, region segmentation, and multi-agent systems. In this section, we describe our approach by explaining its features.

A. Problem Formulation

Given the diversity of segmentation methods, there is no general formulation satisfying all situations. An image I contain several regions R_i : $I = \bigcup_{i=1}^n R_i$, where $i \in \{1, 2, \dots, n\}$. Each region has a uniformity predicate 'Pu' to be tested by agents during the segmentation process as follows:

- Random generation of seed points
- Uniformity predicate evaluation of seed point
- Start neighbors' predicate evaluation
- Repeat
- Select the similar neighbors
- Update contour map

- Select the next seed generation
- Uniformity predicate evaluation of seed point
- Until Satisfying the stop criterion

Most of the proposed segmentation techniques have not been generally adopted for the lack of generalized solution, they just solve a specific situation. indeed, our approach aims to perform segmentation using a Multi-Agent System that operates two different methods in a cooperative way to have preferment results.

B. Conflict Detection

The complexity of the interactions between the agents can lead to the existence of a conflict requiring resolution so that each of the agents can perceive the system, move forward and perform their tasks. First, the detection conflict’s situation can be done at the MAS design stage to avoid conflicts occurred during the execution of the MAS interactions. Second, in runtime, when the MAS agents have to solve conflicts optimally and dynamically. Agents conflicts depend on various factors, such as the ability of the proposed segmentation system to reason about the interactions within the MAS.

A conflict may arise when simultaneous actions are achieved with overlapping values. Each agent can address a conflict situation differently in order to obtain its goals in a reduced time. These agents will manage the segmentation process and monitor the areas around them using communication skills to define if a conflict situation may occur. In our system, agents are free to communicate, interact, cooperate and negotiate for a better achievement of common goals.

As agents try to achieve their goals, conflict can affect decision making and subsequently the quality of the work provided. Negotiation can help agents better explore their neighbors for better decision-making. However, when several agents have an interest in doing the same actions, in the same environment and at the same time, this can cause situations of conflict that can affect decision-making because of incomplete and inconsistent information. Once the conflict situation is triggered, the agents' interactions, as well as the segmentation results, change considerably.

C. The Organization of the Proposed System

1) System Components

The proposed architecture(fig.1) in this article is based on a well-defined distributed organization, which makes it possible to simplify the tasks of the agents throughout the process of segmentation in the image to be processed. To ensure decent management we divided the system into three parts: The Knowledge, the data and the active parts.

i. The Data Part Components

The advantage of having a data part is to quickly compose its visualization of a received image and manage all operating data by the system. This system component tends to collect, store, and process data. Indeed, this part contains the observable aspect and the unobservable (all details related to the image) and can produce huge amounts of data that can be used in

seeking higher segmentation quality or in monitoring the medical image. However, the data part has intermediate data of various types: regional maps, lists of related points, tables of measured values.

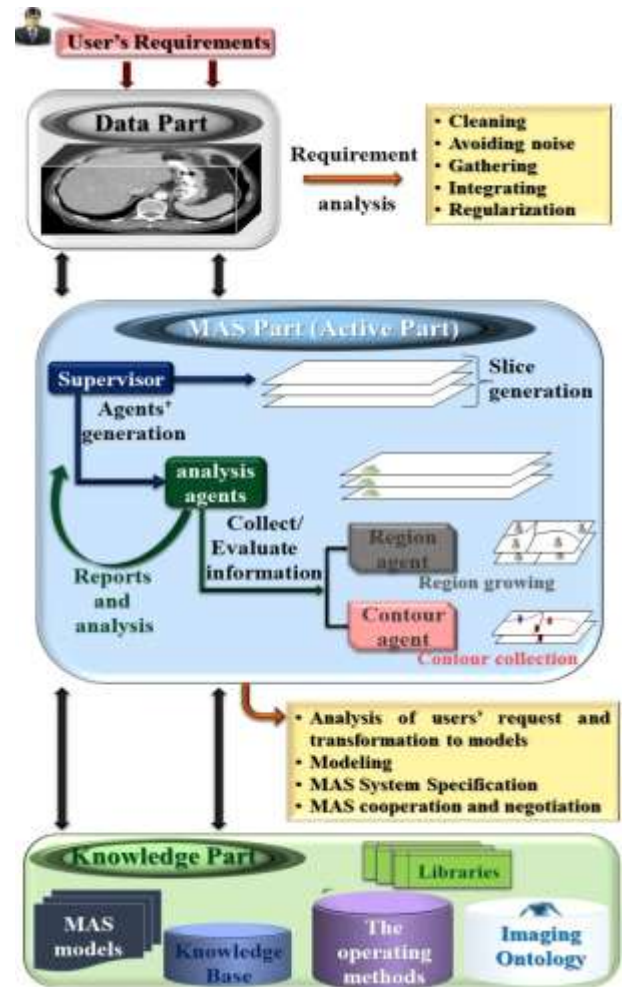


Fig. 1. General proposed architecture

ii. The Active Part Proposals

It is difficult to model an active part configuration in 3D images, due to the non-rigid object, and the different configurations steps. To remove such issues, we introduce the way we model the active part of a 3D medical image segmentation. To this end, we make the following propositions which organize the whole active part:

- 1) The image has to be sliced;
- 2) The obtained slices have to process;
- 3) The obtained results could be collected;
- 4) Each agent has to explore the system and improve its knowledge.

The active set of our system agents, messages, negotiation, ... intended to automate image segmentation. It ensures an understanding of the processes and interactions taking place in the system. This makes the system's efficiency not only sustainable over time, but cost-effective.

iii. *The Knowledge Part Components*

The knowledge part includes all the data, knowledge or representations which are specific to the image processing field, as well as all the basic rules that can be used to simplify the regions of interest searching. Knowledge can be divided as follows:

- The libraries that contain all the routines that can be used to perform frequent operations in system programming.
- The methods represent a collection of processes acting to perform a very specific task. In our system, the principle of cooperation approaches contour/region, as well as the cooperation agent, is realized by using the language Python.
- Information that represents any type of information that can facilitate the image processing in question, such as 2D / 3D image ontology and negotiation protocols in multi-agent systems.

2) *System Architecture*

To properly manage our system, we have referred the ‘Supervisor agent’ which is responsible for performing several tasks including the generation of slices, the analysis agents positioning for each slice, the management of all system agents as well as the collection of results and their analysis. Within our system, different types of interactions can take place:

- Agent / Environment interactions that allow for system exploration, data perception, and receipt of status updates that may occur.
- Agent / Agent interactions represent the possible relations between agents.

Since our method is based on the principles of distributed systems, all agents aim to accomplish a common task. However, the choice of cooperation to properly manage the agent relations is based on the classification of the types as well as the priority of the undergoing situation:

- Stand-off or conflict situation: Agents may experience a confrontational situation during a process of either merging data or results.
- Growth situation: In this case the agent seeks to evolve his skills to better ensure the progress of his tasks.
- Integration Situation: In a complex situation, agents prefer to break it down into subtasks to better overcome difficulties.
- Negotiating situation: During the conflict over resources or the collection of results, agents may move to a negotiation stage to solve problems and improve the quality of results.

3) *The Implemented Agents*

One of the major issues of medical image segmentation is separating exact regions and edges that correspond to an object of interest. To ensure the performance of our approach, we defined the needed agents as explained in the following sub-sub-sections.

i. *Diagram of the Generic Agent*

The use of generic models allows describing the specificity of agents, the description of tasks, as well as the modeling of MAS specific organizations [31]. Each agent contains a generic agent instance, which implements an initial set of capabilities that can be improved through MAS development mechanisms. By applying our method, we focus on pixel detection to segment an image.

A generic agent, as presented in (fig.2), can perform several roles according to the internal state that represents all the system’s information, the list of agents, the goals’ tree, the possible behavior.

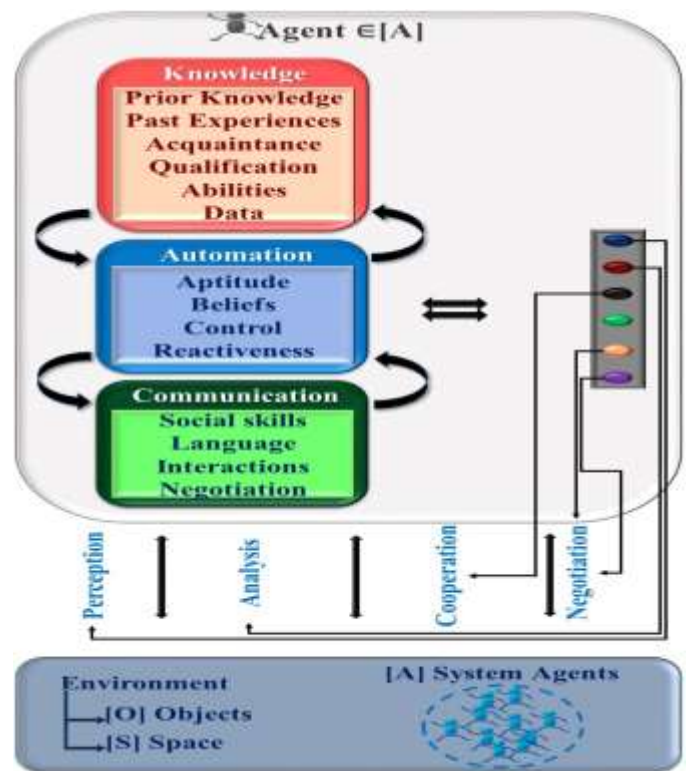


Fig. 2. Diagram of the generic agent

ii. *The Implemented Agents*

Our architecture is inspired by distributed systems, where many agents work cooperatively to achieve a common goal. To better manage the segmentation process, we chose to implement different types of agents:

- The supervisor (S) as well as the controller and manager of the MAS. It is responsible, first, to place an analysis agent AA on each of the slices of the image being processed. Then, it places the segmentation agents either regions or contours in the appropriate areas according to the image map. Finally, he collects the results obtained
- The Analysis Agent (AA) is responsible for producing the global parameters used for the proper segmentation.
- The Segmentation Agent (SA) is responsible for collecting similar criteria according to its type either the region (SAr) or contour (SAc).

The agent's behavior is organized according to two stages. In

the first, each agent identifies all the characteristics of its regions and finds its neighbors on the image. After all the agents had executed this first stage, each agent would then choose a strategy for the next round based on the common goals. The behavior of an agent is triggered due to its aims or other agents' moves, and this trigger behavior is defined as follows: find the neighboring agents, calculates the distance away from the triggered agent.

D. Agent Cooperation

In a MAS, agents are able to interact, communicate with others, share the same goal, progress with other agents for solving the faced issues and helping others to achieve their activities. This requires that agents can allow them to communicate their requirements. Social behavior defines the aptitude of varied agents to communicate and cooperate with others. Moreover, social behavior can be defined according to two main activities: collaboration, cooperation, and negotiation.

Cooperation describes the collective organization that intends to promote a system based on a shared vision of the different agents. Cooperation leads to a revision of the modes of operation as well as the relations between agents. The agents recognize that the best results can be achieved through cooperation and taking into account the status of the other agents with whom they communicate.

The implementation of the contour/ region cooperation (Fig.3) allows achieving the common goals accurately. The agents have a message box to manage the communication exchange with other SAR, SAc, SA, etc. to ensure the coordination of the executed tasks.

Since the segmentation is a cooperative operation, different agents have been implemented. The segmentation agent SA manages contour/ region results cooperatively. Consequently, the agents SAR and SAc operate with others as follows:

- The agent SAR (region segmentation) (Figure 3.a)) is located at first in a seed point, it examines the criterion of homogeneity of this pixel and starts looking for other similar points. For that, SAR has an instantaneous update about region and contour maps, and the neighboring agent in the same slice.
- Every SAc (contour segmentation) (Figure 3.b)) have lists of regions borders and the gradients of regions in the same slice.

To ensure better cooperation we opted for the negotiation which defines the ability of agents to negotiate a specific situation to reach a specific agreement according to their specification [32]. Agent negotiation includes different forms of interactions. During the negotiation process, an agent may not have the accurate information of its neighbors, and the agent may negotiate with its others by using the prior information.

While segmenting an image, system agents can face conflict or disagreement that can block the entire process. For this, we have chosen to define a communication protocol to resolve annoyances.

The protocol adopted allows evaluating the ability to analyze and resolving the conflicts due to the exchanged messages between the agents. According to the negotiation process, we

can figure out that there are different kinds of agent reactions: Inactive, waiting for a proposal, creating a proposal, modifying or refusing a proposal, etc. More clarified negotiation steps would be detailed in the following sections.

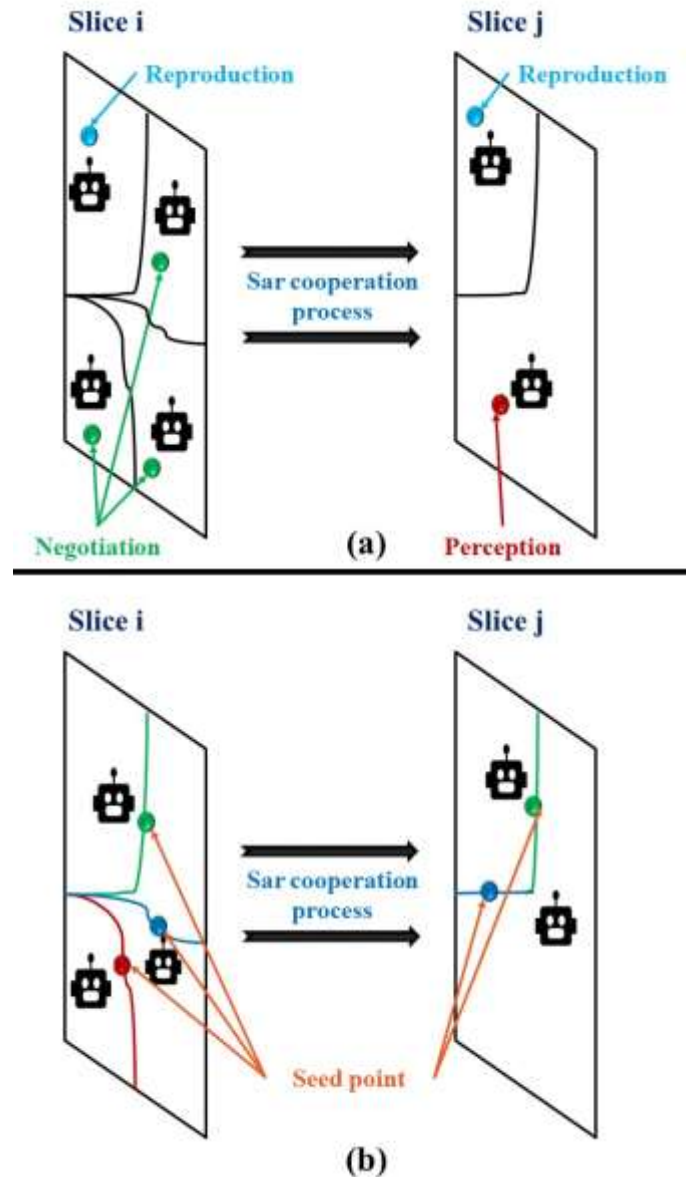


Fig. 3. Segmentation agent cooperation process: [a-Segmentation region SAR], [b-Segmentation region SAc]

IV. THE RESOLUTION METHODS

A. System Organization

Our method provides a MAS architecture for the realization of a cooperative segmentation. We consider the two methods region and contour as complementary to benefit from their advantages and specificities. Indeed, our MAS can experience different interactions. For that, an agent can explore and percept the environment, send messages, collect data, or/and receive updates.

In this MAS (Fig.4) we distinguish a supervisor agent and

several other agents each dedicated to a specific task in the segmentation process. The supervisor agent can monitor the global state of the segmentation system. However, the other agents have to keep it informed using message exchanges.

The supervisor can detect global symptoms and can impose a particular task to agents if it considers this necessary to satisfy the common goals. It has information about the region and/or contour maps and agents' progression. This agent is responsible for performing various tasks:

- Generate and filter image-slices from the 3D image
- Ensure the reproduction by creating a new set of agents to ensure the continuation of tasks.
- Manage message exchanges and analyze agent results.

The supervisor has a global view of the system, but the analysis agents have a local view of the correspondent slice. The cooperation of all the agents allows determining uniform regions and contours, as well as updating image maps.

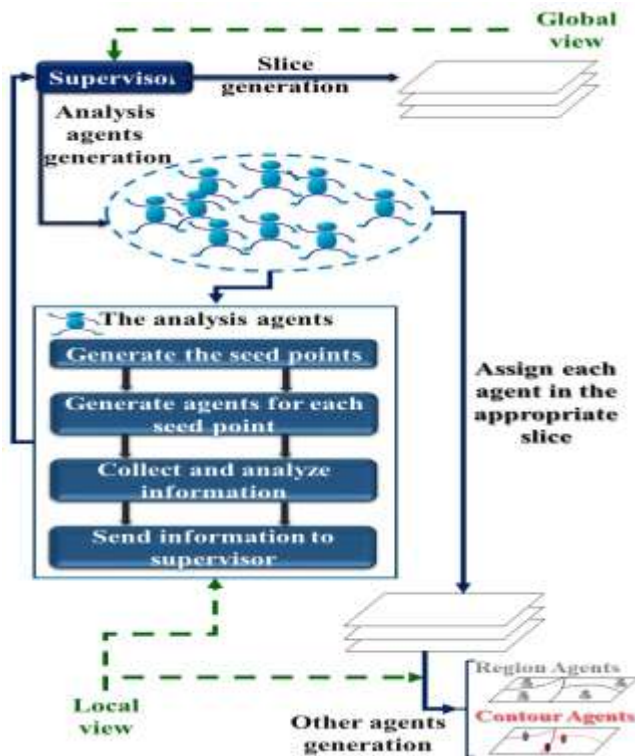


Fig. 4. Our MAS community

B. The Implemented Algorithm

Our choice to integrate two segmentation techniques is based on the purpose to improve the precision of the obtained results. In fact, for each slice, the edge method applies a threshold to determine the seed points and employs an agent for each seed point. Since the algorithm is based on local statistics, the used values in the segmentation process have to be defined. Let I_{ij} the intensity of P_{ij} the pixel situated in the location (i, j) of I_{mn} the studied image.

Yet, to calculate the local average of the gray level Lg_{ij} of

the pixel P_{ij} in a window of size $d \times d$ adjusted at P_{ij} we used the following equation:

$$Lg_{ij} = \sum_{p=i-dm}^{p=i+dm} \sum_{q=j-dm}^{q=j+dm} I_{pq} \quad (1)$$

where:

- (m, n) represent respectively the dimensions of the image I and $0 < i < M$ and $0 < j < N$.
- dm represents the dimension coefficient: $dm = \frac{d-1}{2}$
- d represents the window size.

The variance E_{ij} of P_{ij} is computed using:

$$E_{ij} = \sqrt{\frac{1}{d^2} \sum_{p=i-dm}^{p=i+dm} \sum_{q=j-dm}^{q=j+dm} (I_{pq} - Lg_{ij})^2} \quad (2)$$

The homogeneity criterion Hc of the pixel P_{ij} is calculated as follow:

$$Hc_{ij} = 1 - (dis_{ij} \times E_{ij}) \quad (3)$$

where dis_{ij} is the discontinuity coefficient based on the two components of gradient G_x and G_y according to the point (x, p) :

$$dis_{ij} = \sqrt{G_x^2 + G_y^2} \quad (4)$$

Each neighboring point with the same characteristics must be merged until all the pixels have been processed. Parallel to the progression of the region agent, once a pixel is collected, the region map is updated and the contour agent is informed to progress and update the contour map. Finally, the results of each slice are gotten. Our algorithm uses the equations (1), (2), (3) and (4) to execute the process as follows:

- Step 1. Distinct and denoise the image 'slices'.
- Step 2. Filter each slice; then, compute the median filtered image I .
- Step 3. Accomplish a threshold segmentation
- Step 4. Determine the seed point S_d which is a pixel with a gray value of 255 is considered the seed point for the region. Determine for each pixel the contour class C_c and its average C_{c_av} .
- Step 5. Position the region agent on the seed point. Calculate the homogeneity criterion Hc . Position the contour agent on the middle of each class C_c .
- Step 6. I , S_d , and Hc form the input parameters for region growing computation. Each agent verifies these parameters and calculates the minimum value of each seed point V_{min} .
- Step 7. For each S_d , the region agent and the contour agent verify at once:

- If $V_{min} \ll H_c$, the pixel is added to the expanded pixel queue.
- If $V_{min} \ll C_{c_av}$, this pixel will be added to the contour class queue
- The region and the contour maps are updated.
- Otherwise, the region growing and the contour class collection are stopped.

Step 8.

Repeat (6)– (7), until no more merging or contour collection actions are available.

Step 9.

Each similar region is merged, and its contour is well defined. Then, the region agent and contour agent provide the final maps updates to the analysis agents

Step 10.

The transition of the analysis results of the segmented image to the supervisor.

C. Conflict Resolution Strategy

When an agent selects its neighbors, it only studies the adjacent agents in its observable area and ignores the others. Our MAS fulfills with the fact that the partial information should be shared between the adjacent agents to simplify cooperative decision making. Cooperation is a form of communication-based on sharing information and negotiating the possibilities to achieve common goals. The power to negotiate is a fundamental feature of a MAS environment. The primary mission of the agents is to form an optimal solution that will benefit all components of the agent system. In our system, the definition of negotiating includes all the possible actions that the agents can proceed to resolve conflicts and reach their goals. The interactions, communications, and negotiations of MAS agents are managed using a game theory paradigm, which is Pareto optimum [33], according to their plans, goals, and beliefs. For that, it is essential to define the basic elements for a strong negotiation model that can deal with agents' conflicts.

i. Negotiation Protocol

Agents can negotiate, cooperatively or competitively, with other agents and make merging decisions using protocols and strategies to deal with region merging constraints and advance toward their own goals. Since conflicts situation can occur, we have adopted a restrictive number of negotiation protocols in our MAS. For that, it is suitable to describe the answers that agents can use according to our negotiation protocol based on initial actions such as:

- Accept proposal: Accept a submitted proposal to complete a segmentation task.
- Commitment proposal: the action of submitting a suggestion list containing the solutions to perform, given certain preconditions.
- Terminate: The action to finish the negotiation process.
- Refuse proposal: The agent refuse which is worse than its own situation, or the same.

During our negotiation process, the supervisor will, first, check its own status after receiving new tasks. This agent will

decide to send the segmentation requests to the corresponding region and contour agents. When the task reaches the final commitment, the final optimal solution is obtained. Indeed, negotiation is done via Pareto-optimality which captures the notion of multi-agent rationality.

ii. Negotiation Purpose

The negotiation purpose can cover several problems such as region growing, contour/ region growing cooperation, situation conflicts, deadlines, penalties, communication rules, etc. In the simplest case, the structure and content of a compromise are fixed and the participating agents can either accept it or refuse it depending on the state of the studied merging situation. Subsequently, agents have the opportunity to exchange lists of solution proposals in the negotiating object so that the compromise responds better to the common objectives. Finally, agents might be allowed to dynamically add or remove proposals to validate a common compromise.

iii. Decision Strategy

The decision-making process approved by the negotiating agents. MAS agents have to recommend and exchange their evidence to decide the best solution.

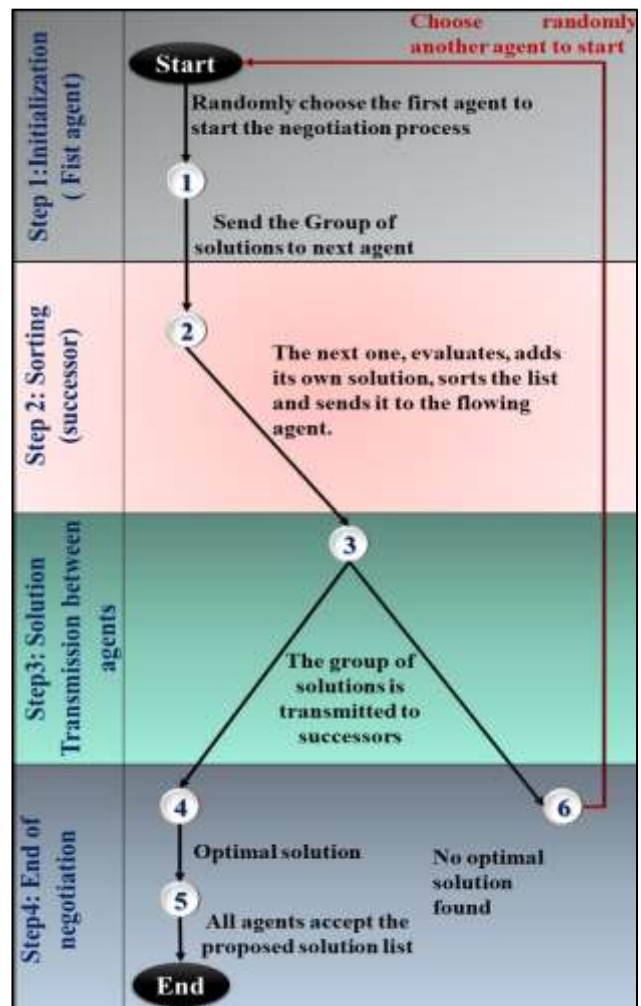


Fig. 5. Conflict resolution strategy

The conflict resolution strategy, based on Pareto Optimum, includes different steps as shown in fig.5. First, an agent, chosen randomly, can initiate the process. This operation puts other start negotiation opportunities on hold. Second, the Pareto optimum allows the evaluation of the possible solution. Third, the solutions' group is transmitted to the nearest agent, which would evaluate the possible solution and transmit the new group to the following agents. In the end, the agents may accept or reject the received solutions. The optimal solution has to satisfy all agents and warranties a better resolution of the conflict.

V. EXPERIMENTATIONS AND DISCUSSION

We evaluated our method on several datasets. Real clinical images were acquired from the Cardiology, traumatology and gastrological Departments of the University Hospital Mohamed 6, Marrakesh, Morocco. For each case, Dicom sequences were tested, comparing our method and w large number of imaging software. to ensure the availability of test images we chose in this article to use a CT example from the open source website [34]. The use of MAS enables the obtaining of more detailed analyses. Conflicts of interest may occur when two potential agents can't cooperate to accomplish their tasks optimally, so that, the global goals could be affected or damaged. For that, communication, especially negotiation is valued to solve problems to obtain a constant segmentation for medical images.

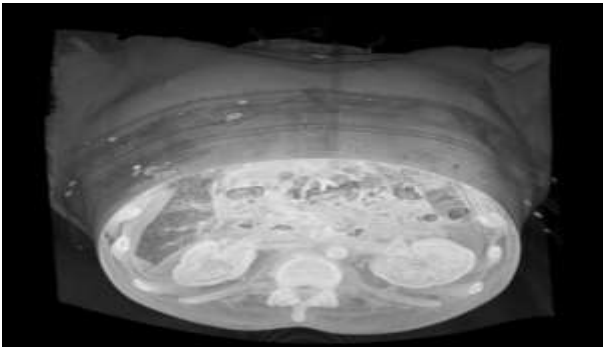


Fig. 6. The studied image

The abdomen 3D image (Fig.6) would be the main environment where agents work together to achieve the segmentation process.

As mentioned in section 2, several works have tried to study the cooperative impact on the segmentation of the image. The work of [35] presented a brief idea about cooperative segmentation. However, in this article, we define each agent based on the pixel map, so that it can communicate and negotiate with other agents in a supervised and homogenous environment.

As a result, we have found that the actions of an agent can influence his social capacity, his reactivity as well as his autonomy. After adjusting the communication rules, we prioritized some necessary interactions and put others on hold according to their importance.

Since our MAS deals with 370 slices the agents' number is enormous so that the interactions. That highlights the importance of distributed tasks, one supervisor controls 370

analysis agents, and each one of them controls an important number of segmentation agents.

A. 3D object Reconstruction

The study of 3D data is considered as a complicated task in image processing. 3D image segmentation can be performed using a different way. Our choice was to make 2D sets from the 3D image so that we can study all agents' interactions to achieve the 3D segmentation task. Indeed, the supervisor is responsible to direct all the executed actions in the system. A first, the slices have to be segmented, so that the required analysis could be completed. Accordingly, the segmentation agent will project its region (or contour) on the adjacent slices and will seek a possible combination with agents having the same homogeneity criteria.

In medical images, 3D reconstruction has gained increasing interest. Our method aims to segment the different slices of a 3D image, then build a 3D object containing the results of the whole process. For that, in a slice S_i , the segmentation agent has to figure out its corresponding results list. Then, this agent will search an acquaintance with the adjacent slices' agents. The Acquaintance defines potential communication between the different agents [36]. Each agent of the slice S_i seeks its correspondent in the adjacent slices: S_{i-1} and S_{i+1} , if there is an intersection between these agents' results, so the acquaintance relationship can occur between them. Each slice can contain various objects. Each 2D object is obtained by the cooperative approach. Certainly, the segmented slices have to be rectified. This leads to 2D sources for the localization in a global environment.

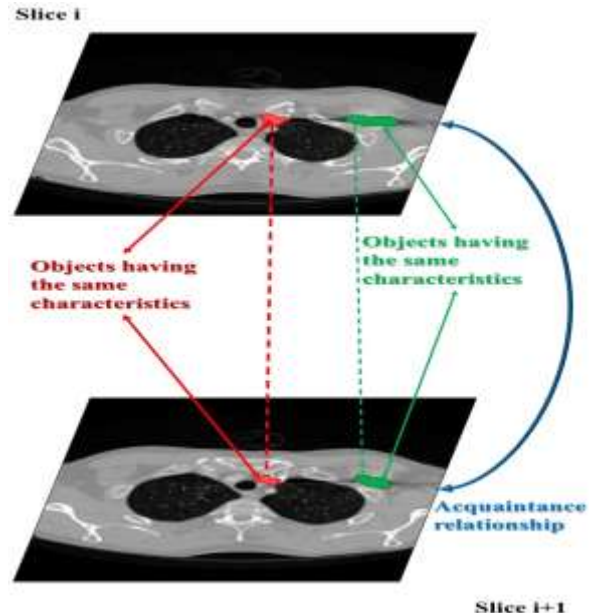


Fig. 7. The acquaintance Relationship

The acquaintance between two agents A_m, A_n can only occur if there is an intersection of regions R or Contours C only if:

$$R_i \cap R_{i+1} \neq \emptyset \text{ and } C_i \cap C_{i+1} \neq \emptyset \Rightarrow \forall A_q(A_m, A_n) \quad (5)$$

where:

- A_m, A_n , are two adjacent agents positioned in the slices i

and $i+1$

- R the region to compare with the adjacent slice results
- C the contour to compare with the adjacent slice results

An object Ob can be constructed only by grouping the sequences of the adjacent results (region /contour):

$$Ob = (\sum_{i=1}^{i=n} U_{j=1}^{j=n} Ri) \cup (\sum_{i=1}^{i=n} U_{j=1}^{j=n} Ci) \quad (6)$$

Fig. 7 makes an implicit assumption: simply, the probability for the depth computed by the agent at any seed point, given those of its neighbors, is the same wherever in the other image slices. This is untrue because the depth of the objects often depends on their positions. Consequently, in some slices, the object can disappear, and maybe another one can take its place. The 3D object is constituted of several parallel slices.

B. Obtained Results

In this section, we present the results from our proposed method. First, we compare the agents' progression through different slices. The second stage aims to confirm if the differences between the algorithms: region growing [37, 38], contour [39, 40], region growing/contour [41, 42, 43], and our cooperative MAS) are significant. So, the second experiment compares different metrics of these methods.

The 3D image can be sliced to 370 slices. To simplify the view of our results, we choose to study the evolution of 4 agents' work during the segmentation process. That choice, allows us to follow the work of agents in different slices and compare the final obtained results for each one. Crossing several slices, we compared the results of the agents (Fig.8). We were able to notice that similar regions were grouped and only a few segments were generated. The progression of these agents can be explained as follows:

- The object can be detected after being absent in several crossing slices (Case of the agent 1).
- The object is present on all the slices, (case of the result found by the Agent2). As the agent is checking its neighbors in the first, it collects the similar pixels in that slice and communicates with its adjacent agent in the next slice, so they can merge their results continues its progress beyond the system.
- The object can appear in a slice and disappear. Then after several slices, the object with the same characteristics appears again (Case of agents 3 and 4).

Another interesting finding is in terms of the numbers of regions, in the sense that using a MAS to ensure the segmentation process can provide better results. For comparison purposes, the values of the proposed approach are evaluated as well as region growing, contour, region growing/contour methods. To demonstrate the efficiency of the proposed method, it is compared qualitatively and quantitatively with the other methods.

Since we are studying slices, we have chosen a slice and

tested with different methods to segment it:

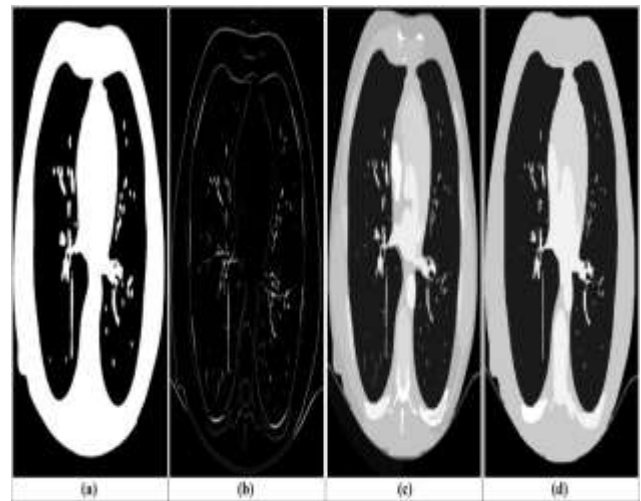


Fig. 9. Methods comparison: Columns show the segmentation results according to different methods: {a=Region growing}, {b= contour}, {c=simple contour/region growing}, {d= The proposed approach}

It can be observed from Figure 9 that for almost all the methods, the final obtained regions using are lesser compared to other methods. However, the subjective comparison shows that the final segmented image obtained through the proposed method is better than that obtained using other methods.

Using the three-evaluation metrics, Table I clarifies that the performance of our method is much better than other methods in terms of sensitivity and specificity. The mean values are above 90%.

TABLE I
QUANTITATIVE COMPARISON RESULTS OF SEGMENTATION PERFORMANCE.

Methods	Accuracy%	Sensitivity%	Specificity%
A = region growing	55,33	56,42	54,91
	±	±	±
B = contour	0,07	09,65	10,11
	±	±	±
C = contour /region growing	59,19	60,81	53,20
	±	±	±
F = the proposed approach	0,31	0,43	11,98
	±	±	±
F = the proposed approach	92,81	92,05	91,33
	±	±	±
F = the proposed approach	0,85	0,27	0,81
	±	±	±
F = the proposed approach	93,51	93,53	92,64
	±	±	±
F = the proposed approach	0,80	5,08	4,01
	±	±	±

Another interesting finding is in terms of knowledge distribution. Indeed, cooperative MAS for medical image segmentation, with both different contour and region growing concepts, can help to better analyze the unseen part of the body.

C. Discussion

In the research field, every study has its limitations and imposes some trade-offs. In this subsection, we discuss if our method may lack reliability or lose the validity of the conclusions reached during this work. First, the lower number of the chosen algorithms to be tested within our approach was based on the methods (region growing and contour) as a central

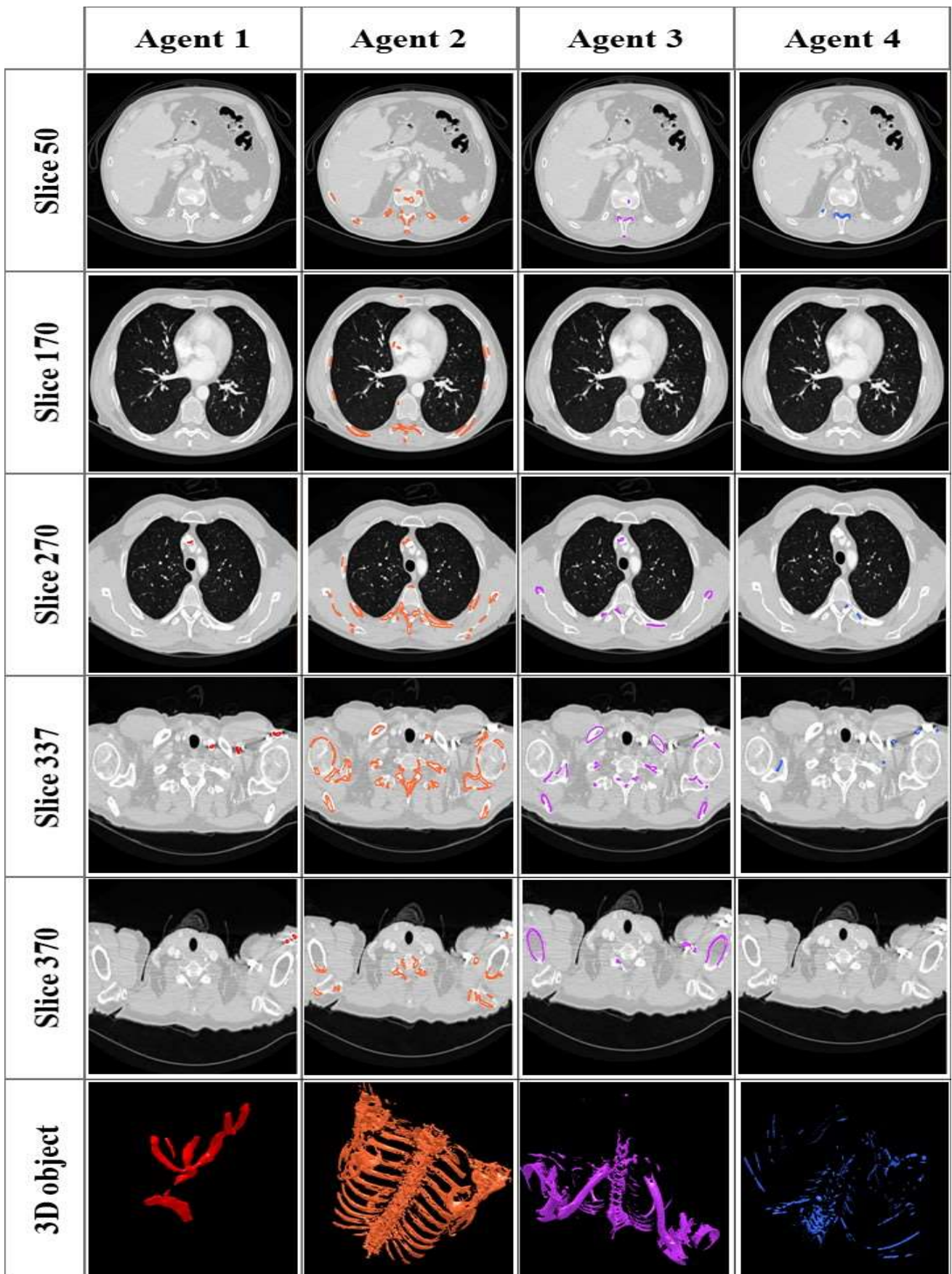


Fig. 8. Segmentation of different slices according to the agent's progression

device for our cooperative segmentation. Second, we adopted an approach to use stable segmentation algorithms, where no many metrics are needed, so they can be easily performed without affecting other parts of the compared methods. Third, the use of only a website dataset. Our DICOM dataset selection can appear to be subjective, but our criterion selection was simple: the images presented were preprocessed. We did this to avoid introducing extra noise. Finally, during those experiments, the results obtained using our proposed method were a little bit similar to cooperative contour/region growing method analysis, compared to other well-known methods, that's due to the interactions between agents. To deal with that treat, in our future work, we are trying to fix rules for the communication between agents to ensure an easygoing system interaction to improve the obtained results.

To demonstrate the potential of this approach, three principal experimentations were made. The results show, for these experiments, a decreasing number of the obtained regions after the segmentation process. In the first experiment, we qualitatively demonstrated the improvement potential of our approach with the comparison between different agents' progression (Fig. 8). In the second experiment (Fig. 9), we proved the strength of our approach with the comparison between the selected methods and our approach (Fig. 10):

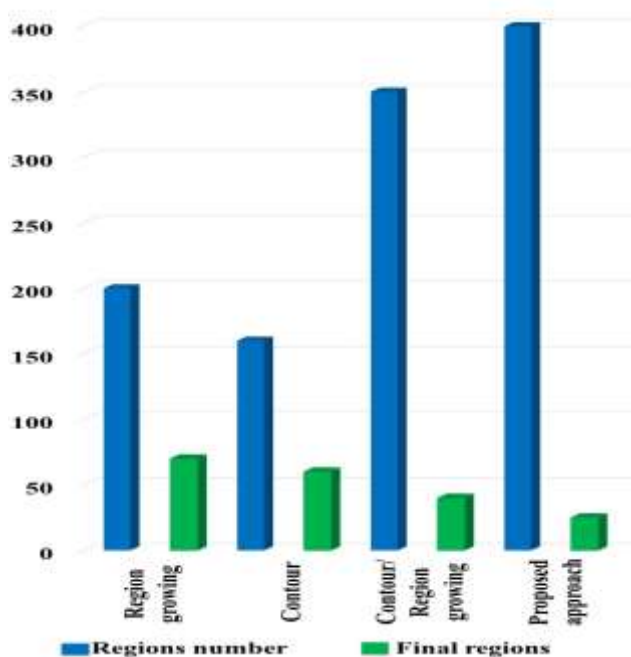


Fig. 10. Methods comparison according to quantitative regions

In the last experiment, we compared the segmentation algorithms based on their execution quantitative results, where we showed that Our approach has an effective range of results. Otherwise, the other methods still have various performances depending on the tested cases and the features of the images. The results confirm the validity of our method of using a cooperative MAS for segmentation using region growing with contour detection.

VI. CONCLUSION

The purpose of this approach was to analyze whether the use of a cooperative method can systematically improve the performance of segmentation, regardless of which kind of the used algorithms. Multi-Agent systems can deal with complex problems, based on distribution concepts. MAS divides a problem into numerous sub-problems to ensure effective results. Our MAS provides a robust method for image segmentation.

In this paper, we have presented an improved method for segmentation based on Multi-Agent Systems to achieve a growing method combined with contour detection. We have introduced a set of rules to direct information transfer beyond the system. Each agent has a self-working region in the slice S_i , this agent, has to check the adjacent slices ($i-1$ and $i+1$) for results' collection respecting other agents' priorities and requests. Firstly, an agent filters the neighboring pixels, it extracts similar pixels, then updates image maps. Secondly, the exchanged information between neighbors has to apply the cooperative rules to deal with all the possible situations. Finally, the agent verifies acquaintance possibilities to form the 3D results.

The quantitative evaluation has been performed. First, the choice of the open source dataset was justified by the possibility of comparing the segmentation results. The proposed method has been also compared to other segmentation methods and it has been shown that it generates better performance.

Even if this study is only a first step in a series of possible empirical evaluation studies employing other segmentation methods and different metrics, it has shown strong evidence that the use of our cooperative method can be considered as a general-purpose applicable improvement. More experiments can be performed extending the original versions of the algorithms employed in the experiments and employing several datasets of images of different kinds, not only the MRI images. Also, different color spaces would be experienced in further experiments.

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