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A robust multi-agent Negotiation for advanced Image Segmentation: Design and Implementation

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Abstract It is generally accepted that segmentation is a critical problem that influences subsequent tasks during image processing. Often, the proposed approaches provide effectiveness for a limited type of images with a significant lack of a global solution. The difficulty of segmentation lies in the complexity of providing a global solution with acceptable accuracy within a reasonable time. To overcome this problem, some solutions combined several methods. This paper presents a method for segmenting 2D/3D images by merging regions and solving problems encountered during the process using a multi-agent system (MAS). We are using the strengths of MAS by opting for a compromise that satisfies segmentation by agents' acts. Regions with high similarity are merged immediately, while others with low similarity are ignored. The remaining ones, with ambiguous similarity, are solved in a coalition by negotiation. In our system, the agents make decisions according to the utility functions adopting the Pareto optimal in Game theory. Unlike hierarchical merging methods, MAS performs a hypothetical merger planning then negotiates the agreements' subsets to merge all regions at once.

Keywords: Image segmentation, Region merging, Multi-Agent System, Game Theory, Coalition, Negotiation.

1 Introduction

Image segmentation indicates the partitioning process of an image into regions of interest by following a set of given criteria. This is concerning the different characteristics of the image such as colour or texture [1]. Image segmentation is applied in many applications such as object recognition [2, 3], target tracking [4], content-based image processing [5] and medical image processing [6, 7, 8]. Generally, the segmentation is about producing numerous partitions(segments) having homogeneous characteristics, then group the significant parts. Many studies and works related to image segmentation, utilized region concept as a significant pre-processing stage. The region is an image concept that is simple and more resistant to noise in segmentation algorithms [9].

The main purpose of region techniques is to join regions having the same homogeneity criteria. However, these approaches don't have a strong determination of the natural limits of the objects due to their less satisfactory results concerning the preservation of the global properties. For that, cooperative segmentation provides an additional advantage, combining several methods or algorithms, to achieve reliable results in less time. Otherwise, cooperation remains an important property of multi-agent systems, it involves the collaboration assumptions, negotiation plans, and resolution conflicts strategies. MAS [10, 11], have proved better results, as they take into account the characteristics of the entities in the image.

The objective of this paper is to implement a cooperative image segmentation algorithm, based on the concept of region merging, where similar neighboring regions are merged according to a novel process. After being placed on regions, the agents can decide the merger under some constraints that satisfy similarity predicates. Principally, we are interested in the use of MAS in the 2D/3D region segmentation. This proposal aims to apply several principles among the model agents (communication, coordination, negotiation, and cooperation), whose objective is building efficient segmentation. Adopting cooperation between segmentation techniques improves the quality and reliability of analyzes and possible decisions [12].

Our adopted mechanism to solve conflicts uses agent negotiation which is based on game theory techniques [13, 14, 15]. In our system, the most important stage is the region merging decision. Agents are organized in a

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neighboring structure according to the region adjacency (RAG) [16, 17]. Each agent proposes a merging plan (set of merging regions) which is transmitted to all its neighbors. Next, the closer neighbor evaluates the received plans and decides to accept or reject the hole plans or a specific plans' subset. The retained subset of all proposed plans will be the compromise between all neighbors. Our experimental results indicate the effectiveness of the proposed algorithm.

This paper will be organized in the following sections: In section II, we specify the related works about cooperative segmentation. In section III, we explain the adopted segmentation modalities. In section IV, we present the general resolution approach. In section V, we clarify the experimental results. Finally, in section VI, we provide a conclusion of our paper.

2 Related works

2.1 About region segmentation techniques

In the field of image segmentation, region-based approaches normally apply various protocols. For instance, region growing [18] is based on the seed points to establish similar neighboring grouping pixels [19]. Splitting and merging techniques are wildly used in the image segmentation [20]. The principle of “region segmentation” is based on the combination of the regions Ri in a way to form an image I=U R_i with i = {1,2,3, ..., n}. If there is no match between the two regions, then no merging action is possible. In image segmentation, many techniques have been used such as superpixel, region growing, region splitting and merging [21]. Whereas, the region growing technique is based on the growing of seed points in order to acquire several homogeneous regions [22]. However, its major drawback is the difficulty to select the appropriate initial seed automatically, and, to deal with the noises and regions with holes form [23]. Region merging aims to join sub-regions together to produce a meaningful merge.

Most methods use over-segmentation results to determine the initial regions. After that, according to a certain criterion, the segmentation is carried out by merging the similar neighboring regions. Whereas segmentation is achieved by making local decisions, some techniques have been shown effectiveness [24, 25]. In region merging techniques, the objective is to merge regions that meet a homogeneity criterion. In previous works, there are region-based fusion algorithms based on statistical properties [24, 26, 27], graph properties [28, 29, 30] or spatiotemporal similarity [25].

Through decades, several leading works of cooperative segmentation have been made. The cooperation of edge\ region-based [31, 32], self-organizing maps (SOMs) \ fuzzy C-means (FCM) [33], watershed \ region merging [34], regions\contours [35] …The main advantage of these cooperative imaging methods is to provide results with a high-quality level. In fact, each method represents a set of limits. For that, combining methods, techniques, or even tasks have been subject to different scientific works to reinforce the systems, and to ensure a good quality of the proposed solutions. For instance, Authors in [36] proposed an active contour model using hybrid region information. That allowed them to ensure better detection of small structures than the traditional models based on the length of a feature's boundaries. In [37] authors were able to extract significant regions using two steps (K-means clustering and region growing).

Later, authors in [38] presented an approach to improve the segmentation of brain MRI images based on convolutional neural networks (CNN) [39] by optimizing the loss function during training. In the same sense, Lei Bi et al., a stacked of Fully Convolutional Networks (FCN) [40] architecture with multi-channel learning to separate the characteristics of the region of interests, belonging to the background of those who do not, to be able to integrate these channels in final segmentation results. Definitely, rather than sequentially exploiting multiple approaches to improve segmentation, it can be more interesting to run multiple segmentation methods or tasks simultaneously. The whole issue of cooperative segmentation lies in the definition of modes of a combination of different sources of information and their use.

2.2 About Game theory

The Game theory is a challenging formalism that aims to study the planned, real or subsequently justified agents’ behavior in antagonism situations (opposition), and to highlight optimal strategies [41]. This theory is based on the concept of a game defined by a set of players (agents), regarding all possible strategies for each player, also the specifications of players’ gain for each combination of strategies [42]. In order to organize these concepts, several types of games were set:

- Cooperative games.
- Non-cooperative games.

- Finished and infinite games.
- Synchronous and asynchronous games.
- Zero-sum games and non-zero-sum games.
- Comprehensive information games and perfect information games.

As a base of a game, an agent can make decisions and take action. For an agent, the strategy defines a complete plan of possible actions during the game. One of the most useful strategies is Nash equilibrium which is a strategy defined by John Nash [43]. It ensures a steady situation, during the players' interactions. If none of them has the interest to change its strategy, the game becomes stable. That means that no player can change its strategy without weakening his own position [44]. Theoretically, it is a combination of strategies to satisfy each player i.

In a cooperative environment, each agent acts to respond to system needs. However, there is no alternative strategy that improves all the earnings of the agents simultaneously. This can only take place by a Pareto optimal [45]. The optimality of Pareto is considered as an efficiency concept. Thus, no state will be optimized, at least one player can get more gains without the other player. There are many examples of Nash equilibria that are not optimal. A result is optimal if no result allows at least one player to be better without the players losing more.

2.3 Image segmentation and game theory

Historically, few works were interested in the correspondence between game theory and image segmentation. One of the possible reasons is game theory grounding as a principle of economic needs satisfaction. Whereas, the first published work is that of A. Chakraborty et al. [46, 47]. In this section, we will mention several works in this area. Initially, Chakraborty presented an original and remarkable work [46]. It is based on a solid mathematical model integrating game theory with image segmentation by cooperation between the edge detector (active contour) and the Region detector using Markov Random Fields. We consider this work as a reference for our method. Years later, E. Cassel et al. [48] proposed a modified and simplified implementation of Chakraborty et al [46]. This simplification involves the removal of the "Prior Information on Shape to Segment" in the edge detector equation. The authors opted for the "growing region" as a region detector and for the morphological operation "for closure" of the edge detector.

Even in [49] authors proposed an approach to iris and pupil segmentation based on the work of Chakraborty et al [46]. However, this approach is particularly suited to this particular area of application. For this, they integrated the pre-treatment and post-treatment phases in their procedure. In this work, the methods "Growing Region" and "Levels" were used. Later, the works of [50], consist of two individual segmentation approaches (edge-based segmentation only). The authors proposed a supervised algorithm based on game theory and dynamic programming for pulmonary field segmentation, while Kallel et al. presented a game-based approach to simultaneously restore and segment noisy images [51]. Lastly, authors in [52] presented a Polarimetric synthetic aperture radar image classification which is an important and continually developing issue in the automatic analysis of remote sensing data. The regions or over-segments are merged into clusters using a game theory-based approach. In the repetitive game, the region merging problem is conducted by an iterative figure/ground separation.

3 The proposed approach

3.1 Merging region using Superpixels/Supervoxels

Superpixel has become ubiquitous in image processing to group pixels into meaningful regions (Superpixels) [53]. In fact, fast pixel grouping allows fast region merging in order to offer trustworthy segmentation results. Superpixels, introduced in [54], have become an essential part of vision researches. In general, the methods producing Superpixels can be collected into a group based on graphs [55, 56] of pixels (Fig 1), such as Slic [57] and Mean Shift, and evolution of curves, such as Turbopixels [58] and seeds.

In fact, fast pixel grouping allows fast region merging in order to offer trustworthy segmentation results. Thus, in 3D analysis, the Supervoxel is agreed to connect similar voxels in 3D regions. Typically, each superpixel is considered as a non-overlapping region with an adaptive shape [59]. Typically, region merging algorithms have some specifications especially the merging criterion which defines the merging threshold. The choice is to study carefully some global properties for the segmentation results. In fact, we use the Region Adjacency Graph (RAG) [60] to have a global representation of the image. In RAG, the adjacency of two nodes specifies that while the segmentation their corresponding pixels are in the immediate neighbourhood of the predefined threshold. An example of the graph structure is shown in Fig. 1, the initial image has 8 partitioned regions, hence the RAG is shown on the right side.

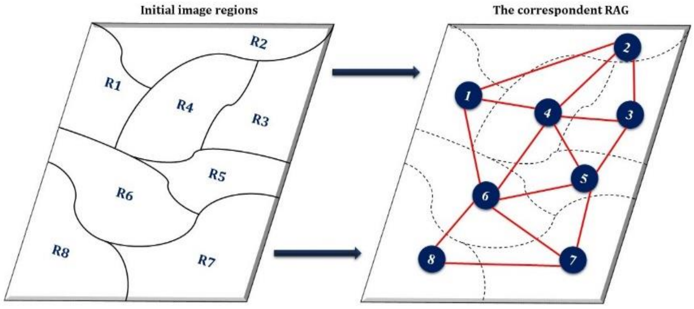

Fig. 1. Region partition and the corresponding region adjacency graph (RAG)

Merging techniques have been the subject of different researches. Previously, the authors explained in [61, 62, 63] that an image can be partitioned, so a set of unconnected regions would be merged to satisfy the similarity conditions. As well in [64], the merge predicate considers the minimum weighting edge between two regions to measure the difference between them. The team of [65] presented an iterative algorithm that considers all similar regions, as well as the gradient image and the edge map [66]. Likewise, [67, 68] proposed a fusion of neighbouring regions following a predicate. Also, the fusion predicate is obtained from the statistical concentration inequalities based on different properties contained in the region. Our initial motivation to use the merging criteria was born out of a pragmatic research methodology: overcome the regions merging deficiencies to obtain objects with more precision.

3.1.1 The merging decision

Selecting the similarity definition between adjacent regions R_i and R_j is an important step, it enables making decisions and obtaining an optimal segmentation result. This similarity can be defined based on the correlation between features or, on some distance definitions. We call the similarity function 'S' so S_{ij} denotes the similarity value between R_i and R_j. Since specifying the threshold value, with tidy precision, remain a difficult task, we assume that a surrounding margin exists around this threshold in case of uncertain decision. For these cases, we define an uncertainty interval, depending on the application domain, limited by two thresholds: a low threshold T_1 and a high threshold T_2. Fig. 2 illustrates this process.

Fig. 2. The merging interval actions

We define the region merging decision strategy (Fig.2):

$$\text{The merging Decision} \begin{cases} \text{if: } S < T_1, \text{then No merging action is applied} \\ \text{if: } S > T_2, \text{then Merge imediatly} \\ \text{If: } T_1 < S < T_2, \text{then no merging decision} \end{cases}$$

In case, the Similarity value is in the interval:] T_1, T_2[all the merging suggestions are considered as uncertain. So, to handle this merging problem, it is important to adopt a cooperative technique, as it is explained in the following sections.

3.1.2 The merging problem

Two questions must be resolved with the above decision:

- How to choose the thresholds T_1 and T_2?
- How to continue the merging process for the remaining regions?

The thresholds (T_1 and T_2) depends on the nature of images and the features used in the Similarity definition. Statistical analyses can be made on some datasets of segmented images (PASCAL VOC [69], BSD500 [70], ...) allow the thresholds' estimation. The implication of Experts of the application domain and images' nature is required to validate the estimation. To continue the merging process, it is necessary to associate all neighbours of a Region and a complement to the defined Utility to refine the decision. For this propose, we consider regions as players (agents) in game theory that can evaluate the merging decision with its adjacency regions but the decisions of all its neighbours too.

3.2 Formulation of the problem using game theory

3.2.1 Game formulation

In Game Theory, the game is a formal model that usually includes a set of players (agents) and different actions or strategies available for each of them. There is a reward for each agent according to the combination of strategies. This approach has been used in computer vision, including clustering [71, 72, 73]. In a cooperative game, agents can cooperate in a predetermined way. A simple form of cooperation allows agents to form coalitions. By acting together in a coalition, agents can enhance their rewards against what they could have achieved by playing according to their personal interests. The problem is to implement a practical coalition structure in order to optimize the overall gain.

a. Basic concepts

In our context, the nodes in the graph (RAG) are replaced by autonomous and dynamic agents. As well, links of the adjacency graph are replaced by acquaintance relations between agents. An acquaintance between two agents means that they are neighbours in the image. This organization represents the region information which is in the image at a particular resolution.

Moreover, regions are characterized by a set of features f_1, ..., f_p. These features are based on:

- statistic features: Means, Variances, Histograms, etc.
- geometric features: Shapes, Boundaries, etc.
- Topological features: Betting numbers (adjacency properties), etc.

Each player (agent) A_i is situated in a Region Ri with information as feature values: v_{i1}, …, v_{ip}. Respectively, an agent A_i has two possible actions: merge (a_1) or not-merge (a_2). To calculate the payoffs or rewards, we consider a utility Function U which depends on features. This utility can be formulated as a combination of mutual motivations like similarity and individual motivation. For instance, for two agents, the payoffs could be illustrated as follows:

		A_j	
		a_1	a_2
A_i	a_1	(u^i_{11}, uj_{11})	(u^i_{12}, uj_{12})
	a_2	(u^i_{21}, uj_{21})	(u^i_{22}, uj_{22})

Where: $\mathbf{u^i_{kk'}}$ is the U value (payoff) for the agent A_i using action a_k and the other Agent using the action $a_{k'}$

- A situation (a^i_{k*}, $a^j_{k'*}$) is Nash equilibrium if: $\mathbf{u^i_{kk*'}} \leq \mathbf{u^i_{k*k*'}}$ $\forall$ k $\in$ {1,2} and $\mathbf{u^j_{k*k'}} \leq \mathbf{u^j_{k*k*'}}$ $\forall$k' $\in$ {1,2}.
- A situation (a^i_{kp}, $a^j_{k'p}$) is Pareto optimal if any other situation can only increase an agent pay-off but reduce other agents' pay-offs.

b. Example of two situations: Pareto and Nash equilibrium

		A_j	
		a_1	a_2
A_i	a_1	(2, 2)	(4, 1)
	a_2	(1, 4)	(3, 3)

- (**a**$_2$, **a**$_2$) is a Pareto optimal but not a Nash equilibrium
- (**a**$_1$, **a**$_1$) is a Nash equilibrium but with no optimal payoffs
- In general, the Nash equilibrium situation doesn't guarantee the optimal payoffs for agents.
- In cooperative games, the Pareto situation is preferred.

For merging decisions, we use Thresholds C_1 and C_2 on utility (based on similarity thresholds T_1 and T_2 with the same term).

3.2.2 The particularity of the utility function

The utility is the policy that prescribes the fact of acting (or not) to maximize the gain of the system agents [74, 75]. Its principle is that the contribution to the general utility determines the value of an action. Thus, the utility evaluates an action (or a rule) only according to its consequences. The utility is the value that an agent gets from the performed actions within the system. Otherwise, a utility function is a representation to define agent preferences for suitable actions beyond the value of the explicit consequences of those actions. In other words, the utility is the measure an agent gets from some chosen actions. To model the utility in a cooperative game, it is necessary to use certain indices:

- The satisfaction rate of constraints relating to the agent,
- Personal satisfaction rate,
- Satisfaction neighborhood rate,
- Total satisfaction rate

3.3 Resolution by coalition

3.3.1 Overview of the multi-agent proposed system

An appropriate way to practice a cooperative game is to use the architecture of a multi-agent system. This architecture offers the implementation of shared knowledge, individual skills, and timely action choices. In our proposed agent-based approach, agents are cooperatively organized to work directly on individual pixels or directly on voxels. In the global approach (Fig. 3), we assume that a homogeneous segment can be specified using a cooperative principle based on MAS strengths.

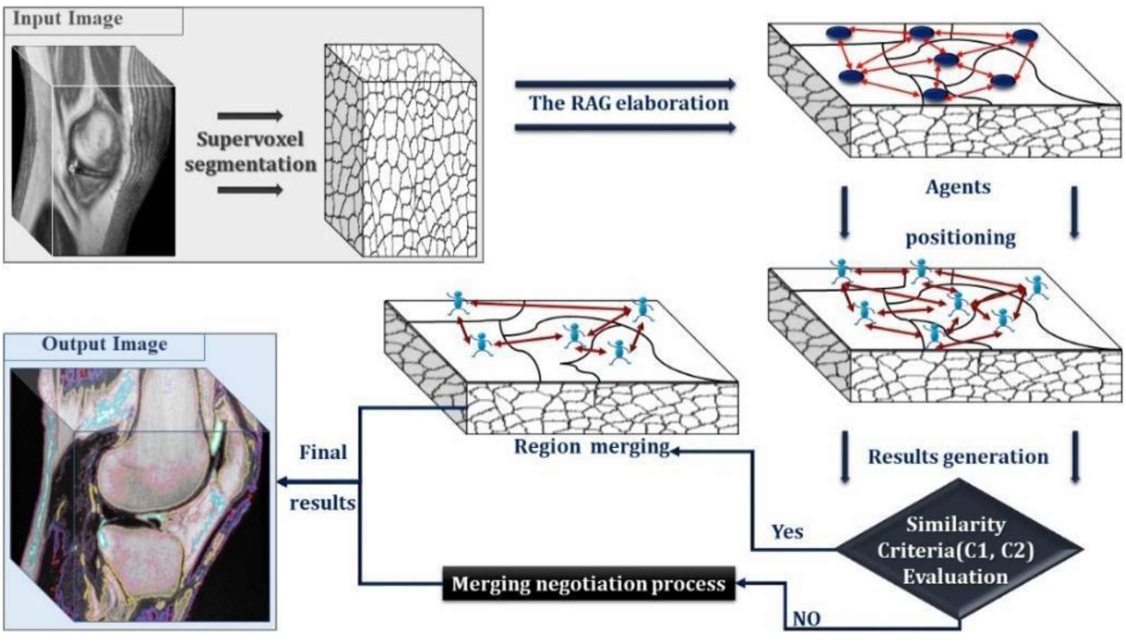

Fig. 3. The global approach

We present a structured vision system architecture as a society of cooperative agents located in the image. In fact, such an architecture is appropriate for ensuring:

- Knowledge and uncertainties integration: the agents provide an attractive abstraction to encapsulate local and intelligent processing. MAS (Multi-Agent System) architectures can be used to organize complex system information which involves several operational and/or descriptive knowledge.
- Local cooperation can be carried out by agents who propagate new constraints locally and information to their neighbors.
- Local adaptations: agents can adapt their behaviors locally according to the context of the image, prior knowledge or any extracted information.

Once placed in a region, the agent launches an investigation to find the adjacent neighbours in order to determine its merging decisions. The decision may vary depending on the following situations: 1) allowed merging, 2) unapproved merging, 3) the merging can occur only with cooperation and negotiation.

3.3.2 General Resolution approach

The connection of the adjacent regions of the RAG leads to the connection of adjacent agents. This indicates that each node of the RAG is examined during the merging process. In fact, in each region, an agent, who perceives his neighbours, is located. The agent's actions can vary during the evolution of his tasks:

- keep his area (R), no merge is possible
- carry out a merge (M) simply or by negotiation (Mn)

The utility function, considered here, quantifies the desire for a merger with a neighbour for an agent. Thus, u_{ij} expresses the desire of the agent A_i to merge with the agent A_j. This utility is based on the similarity of the features of the two regions. Let N_i the set of neighbours of the agent $A_{i.}$ Each agent A_i forms a coalition with its neighbours in N_i to maximize the number of regions to merge. Then, A_i calculates its utilities with its neighbours, orders them in a list L_i $\{(A_j, u_{ij}) / A_j \in N_i\}$ according to decreasing utility and then asks the list L_j of each A_j in N_i. Finally, A_i constitutes 3 sets:

1- Set of solutions where the merger is possible: $L_{ia}= \{(A_j, u_{ij})/ A_j \in N_i, u_{ij} > C_2 \text{ and } u_{ji} > C_2\}$

2- Set of solutions where the merger is probable: $L_{ip}= \{(A_j, u_{ij})/ A_j \in N_i, u_{ij} \text{ or } u_{ji} < C_2 \text{ and } u_{ii} \text{ or } u_{ji} > C_1\}$

3- Set of solutions where the merger is impossible: $L_{ir}= \{(A_j, u_{ij})/ A_j \in N_i, u_{ij} < C_1 \text{ and } u_{ji} < C_1\}$

Taking a decision concerning the merger could be accomplished in two steps:

1) Step 1:

- A_i accepts to merge the regions R_i and R_j for A_j / $(A_j, u_{ij}) \in L_{ia}$ after validation of agents A_i and A_j in a Pareto situation.
- A_i rejects the merger of the regions R_i and R_j for A_j / $(A_j, u_{ij}) \in L_{ir}$.

2) Step 2:

A_i negotiates the merger of Regions R_i and R_j A_j / $(A_j, u_{ij}) \in L_{ip}$.

In this case, the agent A_i must revise its utilities at the level of the list L_{ip} in the sense of strengthening his desires or not. To confirm his decision, the agent A_i first forms a group G_i (a L_{ip} subset) as a set of possible merger solutions according to its new utilities, then checks its neighbors for validation. According to the optimal Pareto situations, the agent and the neighbours seek a compromise to validate (positive reassessment) the group G_i or a part of the group. The negotiation procedure is that the agent A_i sends the group to one of his neighbours (choice to be discussed), the neighbour re-evaluates the solutions and constitutes a new solutions' subgroup that he decides to keep, then it chooses, in turn, new neighbour (among the remaining ones in N_i) and sends him the subgroup and so on. Solutions that remain after the last visited neighbour will be taken into account.

To carry out an image segmentation, distinct regions have to be merged. Generally, a "good qualified" merger must satisfy the following criteria:

- All pixels have to be assigned to regions,
- Every pixel has to belong to only one region,
- Each region represents an associated set of pixels,
- Every region must be homogeneous according to a given predicate,

To ensure good control of the system, the region agent has to send an information message to others at the end of the executed task. The treatment of the messages between agents is according to the following diagram (Fig.4):

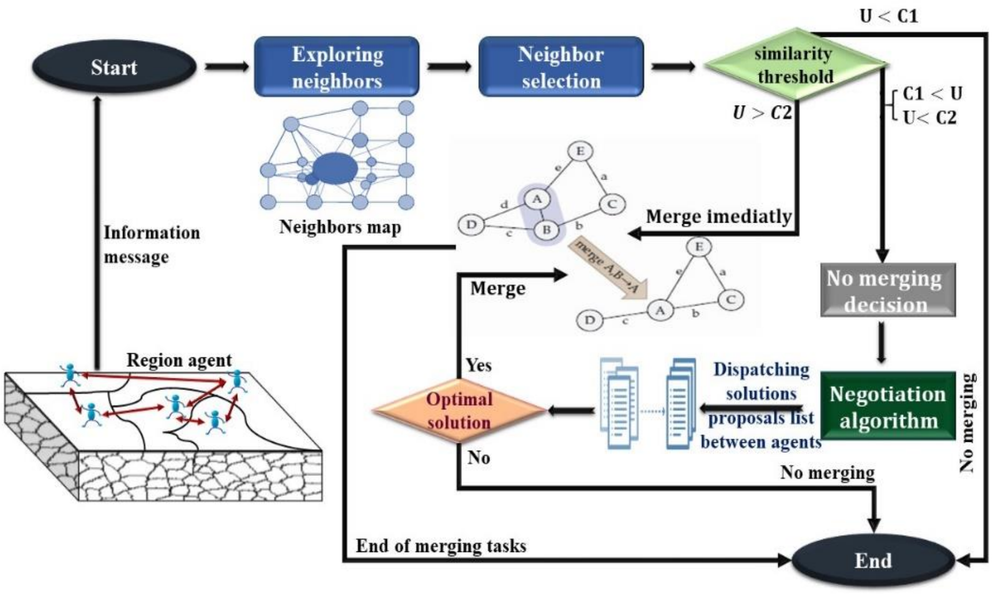

Fig. 4. The proposed approach for region merging process

a. Coalition

The coalition represents a grouping of cooperative agents for the common goal achievement [76]. For this reason, a function called "utility" is associated with different agents forming the coalition. Thus, we seek to model the relations between the different entities. With the utility function, the cooperation problem could be solved in a centralized way according to mathematical models and using the multi-criterion techniques [77]. Our proposal aims to form a coalition of agents that can be included in a segmentation task.

b. Negotiation importance

For an agent, the definition of negotiation must include all the acts to carry on, communication rules, and the resolution of conflicts. Negotiation remains an essential arrangement of interactions managed by a group of agents to reach a mutual agreement according to specific beliefs, goals or plans. Each agent maintains a preference list of the collaborating neighbours. Some elements must be defined to build a model of negotiation by a multi-agent system, for instance, in [78] three fundamental components were identified:

1. Negotiation Protocol collects the rules for organizing negotiation, communication, conversation and decision-making between agents [79]. Since we have adopted a restrictive number of negotiation protocols in our MAS, it is suitable to describe the answers that agents can use.
2. Negotiation Object represents, in our case, all the interactions on which a compromise must be found. The object can contain only one problem (such as merging), while it can cover different problems (conflicts, merging problem, deadlines, penalties, communication rules, etc.).
3. Decision Strategy defines the process approved by the negotiating agents. During the negotiation, each agent develops and exchanges arguments to defend its position or to change it to reach another region. For those who are dissatisfied, or who have not received an agreement simply through the utility test with merger criteria C_1 and C_2, they will form a coalition with agents with the same constraints.

c. Resolution Procedure

The power to negotiate is a fundamental property of an agents' status. Negotiating allow getting optimal solution who is beneficial for the agent and the wholesale system. For that the resolution procedure contains four essential stages:

1. The negotiation Initialization: Agents have negotiation and reasoning skills. However, the negotiation process includes different stages, the start is done by an initiating agent which is chosen based on some considerations or randomly. A task launching puts on hold other agents who are aiming to start a new negotiation.

2. Sorting the received solutions: The adopted principle is the Pareto optimum. So, each suggestion merging solution received by an agent is then reevaluated (in sense of pay-off) and could be accepted or rejected. Consequently, the agent updates the list and sort it according to his preference.
3. Transmission of the solution: The group of solutions is transmitted between the negotiating agents. Once a group of solutions is identified as being a compromise between the courant agent and the earliest agents. The transmission stops if the courant group is empty.
4. End of negotiation: Agents can check all the received solutions, filter them, approve or reject them. If the last group is not empty the agents adopt the proposed merge suggestions.

d. Practical example

In Figure (Fig.5) an example of adjacent agents is shown to explain the transitions to validate a group of solutions and obtain a final compromise. Clearly, it is also a process of exchanges. Studying the case of a neighbourhood composed of 4 agents negotiating the possibilities of merger (green colour). Let Coa the Coalition containing the agents A_1, A_2, A_3, and A_4. we denote u_{ij} the calculated utilities considering its neighbours. The list for A_1:
L_{1p}= {(A_2, u_{12}), (A_4, u_{14})}. The proposed merging solutions are in G_1= {(A_2, u'_{12}), (A_4, u'_{14})} with new utility values. Let's study the negotiation between first agents:

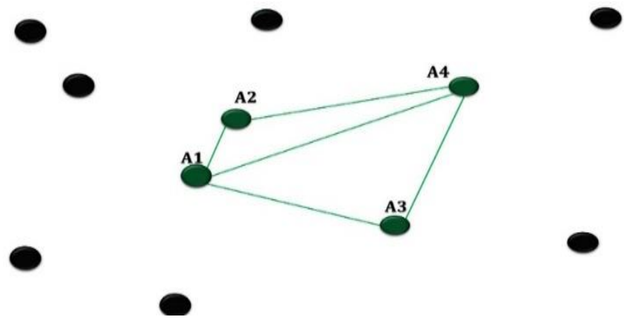

Fig. 5. Example of adjacent agents

If the agent A_1 starts the negotiation process with G_1 the relative proposed solutions to merge with agents A_2 and A_4 after being filtered by new merging criteria.

Table. 1. Example of the possible solutions groups exchange by agents

A_1	-The computed solutions: L_{1p}= {(A_2, u_{12}), (A_4, u_{14})}
	-Order and filtering results with local utility: L_{1p}={(A_2,4), (A_4,9)}
	-Group of solutions by the Agent A_1: **G_1** = {(A_2,4), (A_4,9)}
A_2	-The computed solutions: **G_1** = {(A_2,4), (A_4,9)}
	-Order and filtering results with local utility: **G_1** = {(A_2,6), (A_4,10)}
	-Group of solutions by the Agent A_2: **G_2** ={(A_2,6), (A_4,10)}
A_4	-The computed solutions: **G_2** ={(A_2,6), (A_4,10)}
	-Order and filtering results with local utility: **G_2** ={(A_2,1), (A_4,11)}
	-Group of solutions by the Agent A_4: **G_4** ={(A_4,11)}
A_3	-The computed solutions with local utility: **G_4** ={(A_4,11)}
	-Order and filtering results with local utility: **G_4** ={(A_4,8)}
	-Group of solutions by the Agent A_3: **G_3** {(A_4,8)}

Table. 1 represents the group transfer between these agents. The possible proposed solutions are exchanged through the agent communication to obtain a possible common compromise which is the Pareto optimum. The agent A_1 initiates the negotiation. It sorts all the acceptable solutions in the group **G. A_1** then sends it to the next agent A_2. The group **G_1** contains all the acceptable merging solutions for the agent A_1 because they correspond to a situation as or more satisfactory than its initial reference situation. In the same way, the A_2 agent also looks for its first acceptable solutions, he has its own solutions that can evaluate, and agent A_1's ones so he has to make an order for these solutions in order to form his own group **G_2** that can send to the following agents which would process on the same way. At the end of this negotiation, all agents (A_1, A_2, A_3, A_4) have a compromise for (A_4,8) so they agree with the merge of R_1 and R_4 regions. The figure Fig.6 explains the group transfer between agents A_1 and A_2, A_2 and A_4 and finally A_4 and A_3.

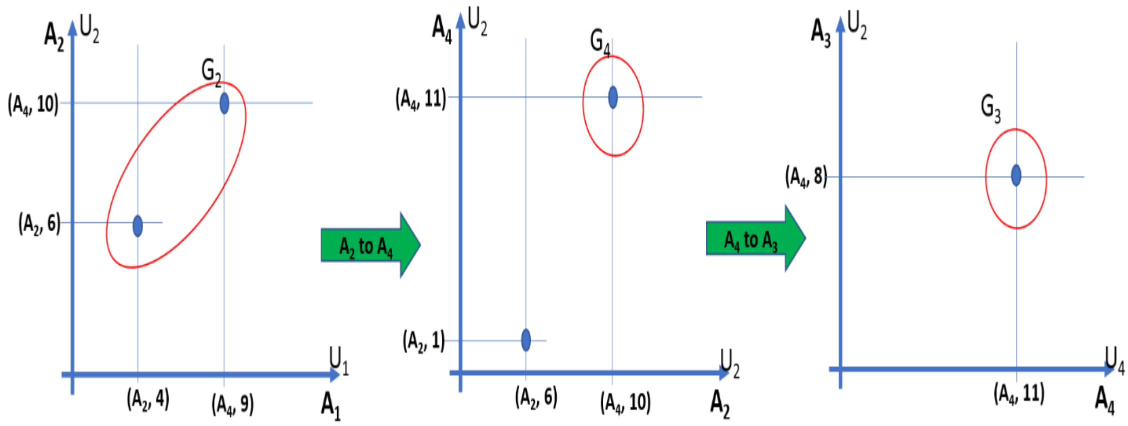

Fig. 6. Graph representing the possible lists of utilities sent by agents

The common objective of cooperating agents is to find a satisfactory solution for all. This example illustrates a small part of the negotiation exchanges between agents in our system.

4 Experimental Results

In this section, we evaluate the proposed architecture by applying the previous steps in python programming and testing different images. To evaluate the quality of a compromise, we introduce here different metrics. Furthermore, our proposed approach for region merging is based on two stages:

- Stage 1: the mechanism of merging is based on similarities according to the threshold criteria C_1 and C_2, then the region map update.
- Stage 2: Since we have a new graph after the region map update, we can use a cooperative approach to negotiate the optimal solution.

4.1 Stage 1: the basic mechanism of the merging process

4.1.1 Determination of similarity criteria

The measurement of the similarity between the pixels along the regions defines the proposed criteria. The choice of these threshold criteria C_1 and C_2 requires specific knowledge and must be done with caution. In this stage, the merging Criteria are the quantitative variables: C_1= 0.06 and C_2=0.824. For similarities less than C_1, the merge is rejected, for these greater than C_2 merge accepted, and for utilities between C_1 and C_2, there is a problem to take the accurate decision. In this case, the region map is updated, a second RAG is obtained after the completed region merging, and the second stage is needed to find the appropriate fusion solution.

4.1.2 RAG construction

One of the strong points of (RAGs) is the spatial view of the image [80]. In fact, the RAG allows us to have a simple view of the connectivity figuring on the image. In order to test the robustness of our method, we carried out experimental data from the Patient Contributed Image Repository [81] We opted for these variant medical MRI images to have the opportunity to compare the results obtained by segmenting images of different cases:

Table 2. The tested datasets specifications

Medical datasets	Number of slices	Type
Knee	124	MR
Shoulder	69	MR
Heart	237	CT

Where: MR refers to Magnetic resonance images and CT refers to the computed tomography scan.

After testing these datasets, different quantitative and qualitative results were obtained. For that, to simplify the presentation of visual results of each of the three datasets, we have chosen randomly a slice then we compared the progression of merging during the execution of our method.

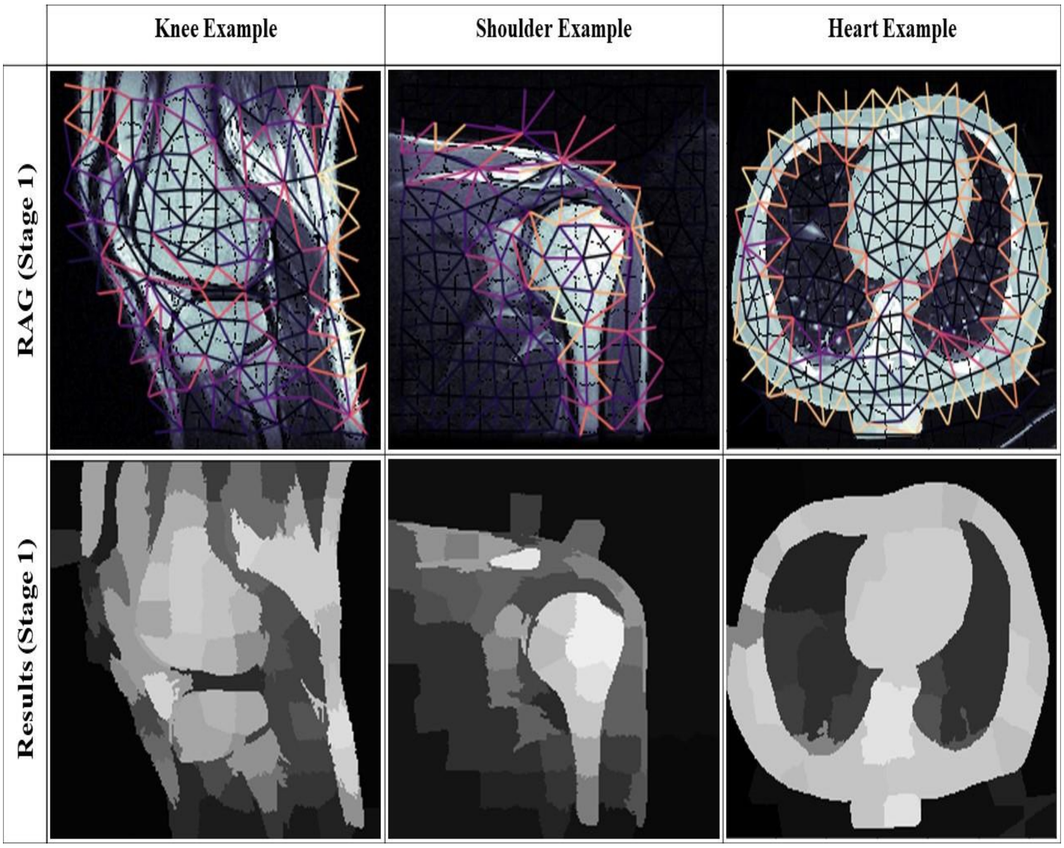

Fig. 7. Stage 1 results crossing the three different datasets

To understand the results of this step, the graph of the chosen examples is displayed in Fig. 7(RAGs-stage1). We can notice easily that the RAGs in this stage contain a huge number of start regions to be segmented. The main idea of our approach is to obtain leading results by merging the numerous regions we have at the beginning. It is quite remarkable, in Fig. 7(results-stage1), there are many resulting regions even more than the observed objects on the studied slices. At this point, we notice the necessity to move to the second stage which is based on a multi-agent system rather than the work of a single agent.

4.1.3 The expression of the used Similarity

The similarity between adjacent regions R_i and R_j can be calculated using weights on RAG arcs and variance measures. Thus, the weights are defined as follow:

$$W_{ij} = \exp\left(-\beta \left(\frac{|h_i - h_j|}{dist(i,j)}\right)^2\right) \qquad (1)$$

Where i and j are two adjacent nodes (regions) of the graph, h_i and h_j are the histograms of R_i and R_j, dist (i, j) is the distance function between the two neighbouring regions, and β is the free integer parameter referring the Euclidean distance.

We can form the similarity $\mathbf{S_{ij}}$ by using a linear combination as follows:

$$S_{ij} = V_{ij} + W_{ij} \qquad (2)$$

Where:

- V_{ij} is the variance measure between the regions i and j.

4.1.4 The Merging Task:

Since the two criteria, C_1 and C_2 need to be checked in order to decide the merge possibility. All the nodes' similarities of the RAG are calculated and stored for each graph layer. Accordingly, an iterative task can be managed regarding the following merging rules:

- If $S_{ij} > C_2$: the merge is accepted,
- If $S_{ij} < C_1$: the merge is rejected,
- Otherwise: no-decision.

The last situation (no decision) can lead to a loss of data from the regions and very possible to the confusion of detection of the good segments. Consequently, for the remaining regions without decision, we adopt MAS decisions by negotiation in stage 2.

4.2 Stage 2: the optimal solution negotiation

4.2.1 MAS adopted architecture

We suggest a merging negotiation framework based on the Multi-Agent System (MAS). This MAS (Fig. 8) consists of heterogeneous types of agents implementing different functionalities in the environment (image). Our system is based on agent applications in compliance with the specifications [83] for an inter-operable intelligent region merging system. FIPA offers, in addition to an agent, a communication language, a specification of the essential agents for the system management, the used ontologies, the behaviour of the agents in the different situations, as well as the compatibility with the platforms of MAS implementation including [84] in Java and [85] in python. The system ontology includes knowledge about the image segmentation, region merging, and game theory concepts. Functional agents can belong to two types: The environment agent and the region agents.

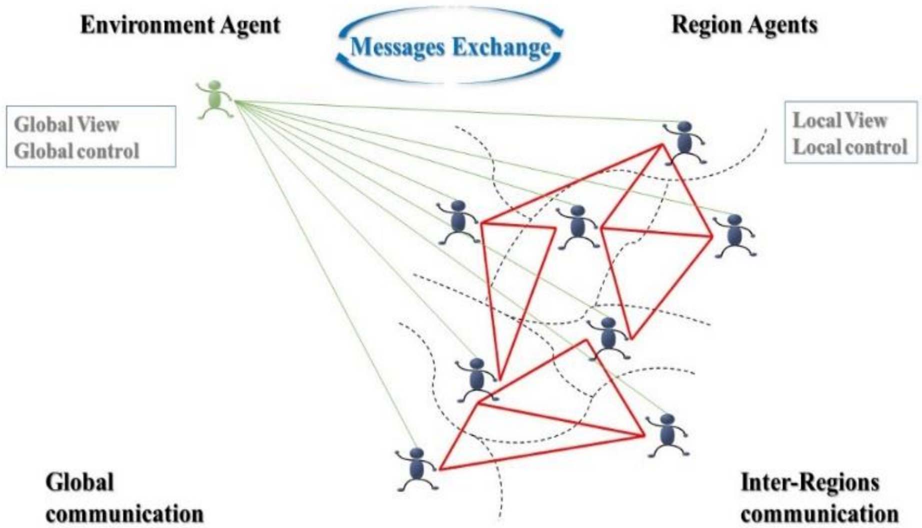

Fig. 8. The cooperative MAS

During this stage, agents' society relies on the Environment Agent and the Region Agents who can exchange and develop the shared information.

a. Environment agent

The environment agent acts globally, with the full ability to reach global system resources, especially the possibility of the exchanged information organization, the results collection, the task distribution, and negotiation management. The Environment Agent has a general vision of the executed tasks. The information it has on regions and agents allows it to properly manage the negotiation process by initializing region agents, according to the results of the functions called at the heart of the process. Its role as the superior in the hierarchy gives him several opportunities using special functions:

- Request update of the list (): allows to rank a list of agents' proposals, which can be updated after each negotiation.
- Request a negotiation (): Triggers a negotiation, so that agents can cooperate and negotiate messages to reach a compromise to resolve the faced problem.
- Approve a merger (): Allows the approval of merger proposals after validation of the results of the negotiation process.

Like all other agents, the environment agent exchanges the messages either to inform others about system changes, the most remaining ones are:

- The initialization of Region agent: The environment agent is in charge of positioning the region agents in the image to be processed and, their initialization to work so agents are listening for new messages.
- The end of negotiation lists construction to a region agent: A negotiation list is formed by the positioned agents.
- The end of negotiation: After agent negotiations, the obtained results are transferred to the environment agent to be approved.

b. Region agent behavior

The region agent is a local actor that performs tasks serving the merge process such as communicating with other region agents, satisfying similarity criteria, and negotiating tasks. These agents are cooperating to improve the merging situation in the system by resolving potential conflicts through communication processes, agent knowledge, and mutual negotiation decisions. In this context each one of the agents has functions allowing it to manage its tasks:

- Do update (): update the list of negotiations.
- Do negotiation (): contribute in a negotiation, by exchanging messages to reach an optimal solution
- Provide merging results (): Send the obtained results to the environment agent so he can approve them or not according to other agents' results.

Having its own skills, and having access to necessary ontologies, the region agent must communicate through messages to inform others about his progression in the system:

- Behaviors ordering: Some functions need a special behavior from the agent or its neighbors.
- Behaviors execution: after defining the action to proceed the agent informs others about the reaction that he will execute.
- Messages handling: the agent must check his messages to be informed about any changes.

4.2.2 The adopted agent utility

Utility [82, 75] is the policy that prescribes the fact of acting (or not) to maximize the gain of the system agents. Its principle is that the contribution to the general utility determines the value of an action. Thus, the utility evaluates an action (or a rule) only according to its consequences. The utility is the value that an agent gets from the performed actions within the system. As mentioned in section 3.3.2, The utility U_{ij} expresses the desire of the Region agent A_i to merge with the Region agent A_j. We calculate this utility using the similarity defined above (S_{ij} in (2)) and agent preferences depending on local information.

$$U_{ij} = S_{ij} * Nbv_i(Lp_i - Lp_j)/E_{ij} \qquad (3)$$

Where:

- S_{ij}: the similarity computed using the equation (2)
- The Nbv_i denotes the number of neighbouring regions for the region R_i
- E_{ij} is the distance average of the two regions R_i and R_j
- Lp_i and Lp_j are respectively the iso-segments describing the distance ranges between the two regions R_i and R_j

4.2.3 The obtained merging results

The merging results of the first stage are used as the input of the second. The negotiation is based on the tests of criteria for decision making. The merge strategy involves an order for the execution of the task. The merging proposals are transferred between the agents, evaluated, and updated until an optimal solution satisfying all the system (Final results in Fig. 9). In our approach, agents interact to accomplish the common objectives and resolve the merger decision issues.

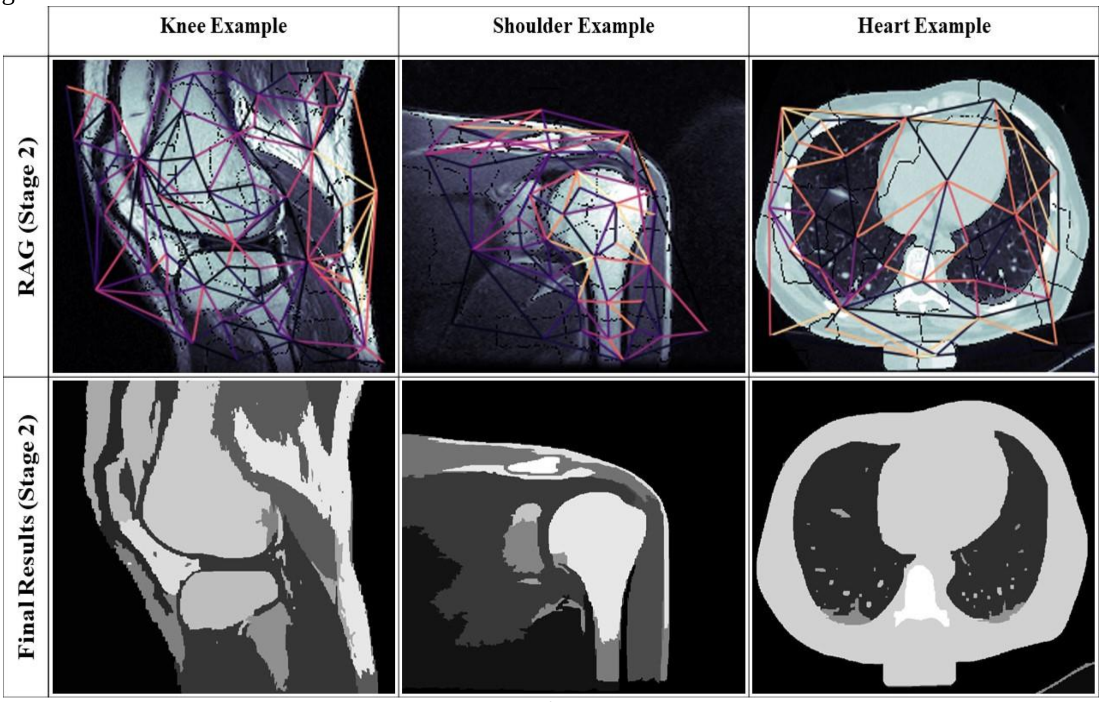

Fig. 9. Results of the second stage

5 Discussion

In the previous sections, we presented our proposed method to resolve a region merging problem. In this section, we discuss the obtained results. Thanks to the multi-agent architecture better fusion quality results were found. Our approach is based on both concepts: agent's negotiation and similarity criteria. Indeed, to evaluate the obtained results we performed several tests. First, the RAGs of the final results as shown in (Fig.10) ensure that we had a tiny number of regions comparing with the RAGs of the first stage.

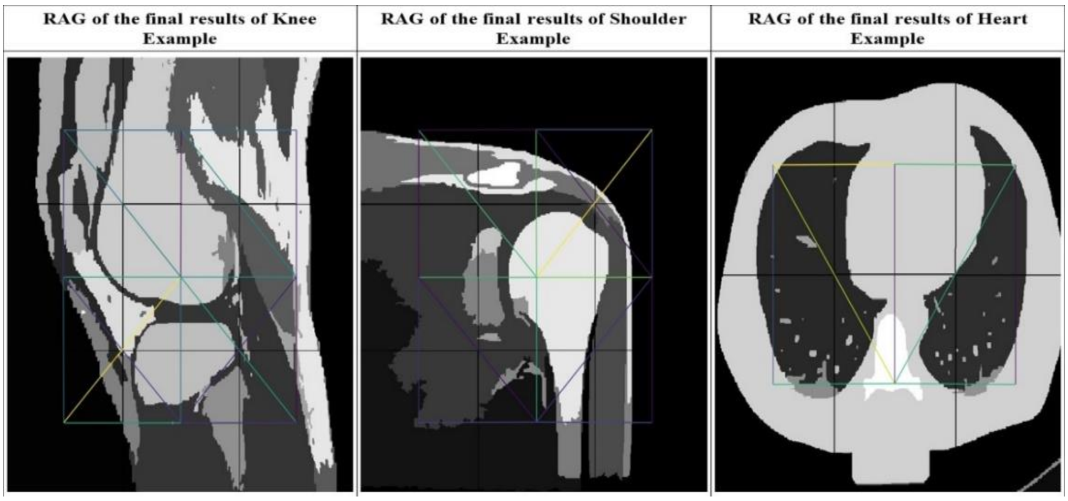

Fig. 10. RAG of the final result indicating fewer regions compared to the starting RAG

The introduced approach in this paper can be implemented to segment different sets of images. The image can be divided into regions and the characteristics of the images can be extracted automatically. In fact, our tests have shown promising results.

In order to show the effectiveness of the proposed method, we evaluated different medical datasets containing Knee, shoulder and heart images. In this part, we quantitatively compare the results with those proven by other methods. First, we tested the results of various methods (including ours) to evaluate their pertinence. Secondly, we classed and compared the methods' outcomes. Finally, we infer the method that offers better results. For that, we used the SSIM [86, 87], F-Measure [88, 89], Dice [90, 91, 92], sensitivity [93], specificity [94] and Jaccard [95, 96, 97] indices:

- SSIM: Structural SIMilarity was developed to measure the visual quality of an image compared to a reference. The idea of SSIM is to measure the similarity of structure between the two images.
- F-measure: Quality index for the results of an image processing that combines the two indices of recall and precision.
- Dice: measures the similarity of the found objects by calculating the size of the overlap of the two segments according to the total size of the two objects.
- Sensitivity: measure the proportion of real positive pixels correctly identified.
- Specificity: refers to the ability of the test to correctly detect pixels that meet the same similarity criteria.
- Jaccard: Measure adopted to evaluate the similarity of a given set. More precisely, it is the ratio between the size of their intersection and the size of their union.

Considering the theoretical properties of possible segmentation approaches into a practical system, our objective in this paper is to present an optimal region-merging approach. However, the efficiency of the proposed method is compared with other methods of image segmentation: Region growing [18], MAS for s Markov random fields (MRF) segmentation [98], and Nash-game approach [51]. To accomplish these tests, the different datasets were tested with the same measures. We chose to test different paradigms to compare the effectiveness of the obtained results by our approach.

Table. 3. The results from methods comparison in segmentation of Knee images dataset

Methods	*SSIM%*	*F-measure%*	*Dice %*	*Sensitivity %*	*Specificity%*	*Jaccard %*
Region growing	74,03	78,56	70,89	67,85	71,46	76,25
MRF segmentation	69,47	77,86	76,10	67;11	74,32	80,76
Nash-game approach	76,46	80,99	73,32	70,28	73,89	78,68
The proposed approach	**88,78**	**90,78**	**86,25**	**84,86**	**87,34**	**92,29**

Table. 4. The results from methods comparison in segmentation of shoulder images dataset

Methods	*SSIM%*	*F-measure%*	*Dice %*	*Sensitivity %*	*Specificity%*	*Jaccard %*
Region growing	***78,67***	***75,57***	***75,67***	***75,59***	***67,12***	***76,10***
MRF segmentation	***67,69***	***75,73***	***69,23***	***66,85***	***71,83***	***75,06***
Nash-game approach	***81,10***	***78,01***	***78,23***	***78,02***	***69,55***	***78,53***
The proposed approach	**89,90**	**91,36**	**90,29**	**88,69**	**85,47**	**90,11**

Table. 5. The results from methods comparison in segmentation of heart images dataset

Methods	*SSIM%*	*F-measure%*	*Dice %*	*Sensitivity %*	*Specificity%*	*Jaccard %*
Region growing	67,23	68,05	70,48	69,83	67,77	71,12
MRF segmentation	65,60	67,73	63,46	65,21	62,67	75,06
Nash-game approach	74,55	75,90	77,30	74,17	71,00	78,23
The proposed approach	**88,69**	**89,73**	**91,07**	**87,91**	**81,66**	**89,00**

To evaluate the effectiveness of the tested methods, we used the same datasets which are open to the scientific researchers on (PCIR) [99], then we carried out a numerical analysis of the qualitative and quantitative results. In particular, we found that segmentation methods based on region growing, and Markov random fields (MRF) provide modest results comparing to other approaches.

Relevant conclusions can be drawn from Tables (3,4 and 5) which compare the results of our proposed approach with the other methods. The table shows a high overall rating and the results from our approach show comparable performances. The other methods obviously have varied performances depending on the tested cases and the features of the images. The results show the validity of our method based on the cooperative MAS for region merging. Indeed, we realized that the performance is always proportional to the calculated utility.

By examining the segmented images, we could notice variable efficiency values from one slice to another, because the high or low slices can have intensities or can contain objects very different from those existing in the middle. Although the comparisons with the obtained segmentation results show evidence that our cooperative MAS produces more efficient segmentation. We noticed that our results became more relevant when we improved the utility in (3). To achieve this, we added another criterion α which is Levine and Nazif intra-region uniformity criterion [100]. This criterion calculates the sum of the contrasts of the regions weighted by their surface So, formula 3 would be updated as follows:

$$U_{ij} = \alpha * S_{ij} + Nbv_i * (Lp_j - Lp_i) / E_{ij} \qquad (4)$$

This allowed us to have the outcomes presented in Table 6:

Table .6. Results of the proposed approach after utility changes for the studied datasets

Methods	*SSIM%*	*F-measure%*	*Dice %*	*Sensitivity %*	*Specificity%*	*Jaccard %*
Knee dataset	91,31	93,27	88,78	87,19	89,77	94,72
Shoulder dataset	92,43	93,89	92,82	91,32	87,91	92,64
Heart dataset	91,11	92,15	93,01	90,33	84,49	91,47

The performance of our method has been increased, as shown in table 6, thanks to the cooperative work of the MAS. However, to obtain homogeneous regions, we need an imaging expert in order to fix the criteria of the merge. Yet, according to our tests, it is a promising idea to start directly through the negotiation stage without leading two successive stages. This can be done by placing the multi-agent system on the image, each agent will progress by calculating its utility function U and communicating its results to the environment agent. Then the environment agent will test each utility according to the similarity criteria C1 and C2 to make a merging decision. After this step, we found that the stronger the utility function, the higher the efficiency of the system. By improving the utility function, we also show that the method can easily be extended by integrating other particularities to improve its performance.

Different challenges have been met to ensure an optimal solution. First, the proposed image segmentation approaches were generally based on the Nash equilibrium to deal with agents' communication. However, in a non-cooperative game, the optimality can't be achieved by only using the Nash equilibrium. For that reason, the negotiation between agents remains a strong solution especially using the Pareto optimal to reach the optimal solution. Second, the size of the proposed prototype and the number of the exchanged messages during the negotiation slow down the execution. But this problem was overcome by adopting lighter agent architectures with certain tasks parallelization. Moreover, it's crystal clear that the number of the negotiated regions is often smaller than the first Superpixels/Supervoxels outcome thanks to agents' work. Finally, the non-compromise case can affect some real mergers, for that, the agent payoffs (utility) must be carefully chosen to improve the quality of the obtained results.

6 Conclusion

This article proposes a new cooperative segmentation considering the exchanged information by the system agents based on the Pareto optimal to improve the performances and to reduce the calculation cost of the MAS. Our studies address the issues of image segmentation to produce a generalized approach. We defined a relevant approach that leads to pertinent results. We believe it is an opportunity to perceive the effective functioning of leading principles of game theory and MAS cooperation. Thus, these principles are adopted in a concrete situation of image segmentation using region merging techniques. The purpose of our study was to study the different combinations of image segmentation techniques. In our case, the adopted principle was the Pareto Optimum which favours the optimum gain.

We have studied and proved that a well-defined approach based on a cooperative Multi-Agent System can improve the continuity of the researches in medical image segmentation. We have also examined that the agents' behaviour can influence the results significantly. Since conflicts can occur while agents are executing their tasks the negotiation remains an important operation to ensure the effectiveness of the segmentation system. Consequently, the main difficulty we faced was the specification of consistent merge criteria. In order to accomplish a satisfactory segmentation, we believe image experts' opinions would help in eliminating ambiguities in all the criteria.

The results have shown that the proposed method is effective and robust in the cooperative segmentation of medical datasets. Eventually, our method offers competitive results with machine learning algorithms that are subject to current trends in image processing.

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