Multi-Agent Medical Image Segmentation: A Survey

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Abstract

During the last decades, the healthcare area has increasingly relied on medical imaging for the diagnosis of a growing number of pathologies. The different types of medical images are mostly manually processed by human radiologists for diseasesâĂŹ detection and monitoring. However, such a procedure is time-consuming and relies on expert judgment. The latter can be influenced by a variety of factors. One of the most complicated image processing tasks is image segmentation. Medical image segmentation consists of dividing the input image into a set of regions of interest, corresponding to body tissues and organs. Recently, artificial intelligence (AI) techniques brought researchersâĂŹ attention with their promising results for the image segmentation automation. Among AI-based techniques are those that use the Multi-Agent System (MAS) paradigm. This paper presents a comparative study of the multi-agent approaches dedicated to the segmentation of medical images, recently published in the literature.

Keywords: Medical Images, Image Segmentation, Multi-Agent Systems, Review, Survey

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1. Introduction

Over the past few decades, the world has been subjected to a new digital revolution transformation. The many recent advances in hardware electronics have led to the proliferation of computers in virtually every field of endeavor. Thanks to software developers, hardware engineers, and researchers, computers have gradually become man's best tools, capable of performing more complex operations. As a result, computers remain isolated units performing a given task individually. Moreover, some problems were unsolvable by a lonely unit and required cooperative solutions. This situation has gradually become more prevalent with the democratization of the Internet, the exponential multiplication of interconnected software systems, and the considerable progress made in robotics and the Internet of Things. These advances were among the many factors that led to the emergence and the generalization of the Multi-Agent System (MAS) paradigm.

MASs have emerged from the collaboration of several disciplines, such as artificial intelligence, distributed systems, and software engineering. Thus, the resulting paradigm has provided new problem-solving mechanisms based on the interaction and organization of several computing entities. These interacting entities cooperate to accomplish a specific task, which usually represents a step towards the accomplishment of the system's objective. Therefore, the multi-agent paradigm provides a collaborative vision for problem-solving.

Several multi-agent techniques have been developed in many health domains, including assistive living, diagnostic, remote physiological monitoring, smart hospital, and smart emergency applications [1]. However, agents are mainly used to manage interactions and consistently monitor cooperation between heterogeneous systems. They can also perform a particular task, thus offering a new perspective to problem-solving. Furthermore, MASs can facilitate a solution's integration into a larger and more complex system thanks to their adaptability. Among this category, we can find MASs designed for medical image segmentation.

Agents are a modern trend in medical image segmentation, many studies have been published in this area. However, the developed techniques still suffer from drawbacks, such as the user manual intervention. MASs provide a collection of characteristics that allow the development of new image segmentation techniques to overcome some of the encountered drawbacks. As a result, many papers on image segmentation have been published recently. Therefore, this paper provides an overview of the recently published works on MASs for medical image segmentation, according to the following organization: Section 2 provides a brief summary of the MAS paradigm. Section 3 describes the methodology followed for the elaboration of this study. Then, Section 4 presents the state of the art of MASs for image segmentation. Section 5 describes and analyses the state-of-the-art multi-agent approaches for medical image segmentation. Some limitations of the reviewed systems are thus detailed in Section 6. Lastly, the paper concludes by providing some possible perspectives for the multi-agent medical image segmentation research area.

2. Multi-Agent systems

As summarized by Bradshaw in [2], since the beginning of recorded history, people have been fascinated with the idea of non-human agents which can facilitate and even automate tasks usually accomplished by human beings.

In the mid-1950s, the idea of a software agent was originated by McCarthy. At the end of the 1970s, the concept of the software agent was, for the first time, formally proposed by Hewitt as a self-contained, interactive, and concurrently executing object that he termed an "actor". Such a concurrent actor was designed to consist of several internal states, a behavior, and a mail address with which it can communicate by message-passing with other actors to carry out their actions concurrently [3].

Since the end of the 1970s, different versions of agent definitions have been given following the rapid evolution of agent research. Among them, we cite the ones widely accepted within the *autonomous agents and multi-agent systems* community research.

- Shoam's definition [4]: «An agent is a software entity that functions continuously and autonomously in a particular environment, often inhabited by other agents and processes.»
- Ferber's definition [5]: «An agent is an autonomous, real or virtual entity, which is capable of acting on itself or its environment, which can communicate directly with other agents, which is driven by a set of tendencies in the form of individual objectives or a satisfaction function that it tries to optimize, and whose behavior is the consequence of its perceiving in its environment, its knowledge, and its interaction with other agents.»

From those two definitions, we can see that an autonomous agent is characterized by several essential features that distinguish it from other traditional AI technologies, such as:

- Autonomy: An agent can modify its internal state and execute its actions, according to its objectives, resources, and capabilities, without external intervention.
- Sociability: An agent can use an agent communication language to interact with other entities (agents or humans). Sociability is essential when the system needs the explicit cooperation of agents.
- Reactivity: An agent can respond to its environment stimulus by acting, changing its goals, or internal state.
- Pro-activeness: A proactive agent is capable of rationally directing its behavior to achieve goals.

Moreover, a MAS is a collection, organization, or society of individual agents with their knowledge, goals, and capacity for action. These agents can dynamically form interest groups and interact in a shared environment, where they can act together for a common purpose [6].

With their characteristics and unique features, MASs offer several possibilities to address complex problems such as image segmentation. Consequently, several original approaches using MASs for image segmentation were published during the last decades. Most of them are reviewed in the following sections.

3. Methodology

For the elaboration of our survey, we considered a variety of peer-reviewed research articles. The different steps involved in this process are:

3.1. Existing surveys

Few surveys addressed multi-agent image segmentation during the last decades, and even fewer were specific to medical image segmentation. Since 2010, only three papers have addressed multi-agent image segmentation literature review.

The first survey, a journal paper published in 2011 by Mishra et al. [7], is a short paper of four pages. It addresses the MAS image segmentation in general. It briefly describes a list of approaches. It provides neither the advantages and issues of the listed approaches nor a discussion.

The second survey [8] also addresses MAS image segmentation. It provides more details. However, it suffers from the same issues of absent advantages and disadvantages lists of the treated approaches.

The last related survey was published in 2022 [9]. In this paper, the authors address general medical image techniques and methods. Thus, even if it describes the MAS principles and offers a discussion section, the paper does not focus on medical image segmentation using the MAS approach.

During our research on existing surveys, we observed the absence of a detailed literature review addressing the multi-agent medical image segmentation works. Therefore, we introduce this survey paper.

3.2. Search Strategy

When selecting the articles to process, we first focused on conference and journal peer-reviewed articles published in the last 25 years that perform image segmentation using multi-agent systems. Using the keywords "multi-agent image segmentation, agent-based image segmentation, cooperative image segmentation,"

we performed an exhaustive search on different databases of research articles, including Scopus, Pubmed, ScienceDirect, ACM library, ... This search resulted in a large set of papers that required refinement. We thus have discarded all the articles that did not explicitly use the agent paradigm in the segmentation process. These articles include both articles dealing with medical image segmentation and the segmentation of other types of images, such as satellite images.

We therefore removed all articles that did not explicitly use the agent paradigm in the segmentation process. We also discarded articles that were too short or did not provide enough details on the approaches considered.

This refinement thus restricted our study to 73 articles. These articles include articles dealing with both medical image segmentation and the segmentation of other types of images, such as satellite images.

3.3. Papers' analysis

When processing the selected articles, we first divided them into two categories: those dealing with the segmentation of medical images and those dealing with the segmentation of other types of images. Then, we proceeded to the detailed analysis of each article according to several criteria, including the type of used agents, the type of processed images, the segmentation method used by the approach, and the need for prior knowledge. The resulting study is described in the following sections.

4. Multi-agent image segmentation

In the last decades, the democratization of digital image analysis has led to increased image processing research, with a great interest in image segmentation. Computer science researchers have thus started to study how to automate this segmentation process using different approaches, including the classical approaches presented in the literature [10]. The focus was on artificial intelligence paradigms to address this automation problem. One of these paradigms is MAS. Different multi-agent approaches have thus been proposed for image segmentation. This section presents some of these works according to the type of image they deal with.

4.1. Multi-agent approaches for photographic image segmentation

Kagawa et al. proposed in [11] a multi-agent approach for natural color image segmentation based on mobile reactive agents. This multi-agent approach performs image segmentation in two phases: region segmentation and region integration. During the region segmentation phase, the agents explore the image to detect its regions. The agent detection behavior operates according to four steps: region characteristics calculation, agent moving, update of the agent characteristics, and agent vanishing. Therefore, this region detection behavior involves a pixel exploration and labeling procedure according to a predefined similarity criterion. This behavior also integrates a pheromone mechanism to optimize the agents' movements. Thus, the region detection phase results in a set of zones. They are then tested for mergeability during the region integration phase, where adjacent regions are merged if they satisfy a merge predicate. Finally, the behavior stops when no more merging is possible in the system. The authors performed their experiments on a set of four natural images. Although the approach presents an interesting artificial life strategy for image segmentation, it requires the calibration of several parameters, and only visual segmentation results were provided. Moreover, the use of an "agent activity" metric to compare the segmentation results lacks relevance since this metric is not related to the quality of the segmentation results.

Ballet et al., in [12, 13], described a new multi-agent approach for edge detection. The system is based on a set of mobile reactive agents that explore a 2D gray-scale image in search of gradient extrema (corresponding to edges). The agents thus use a set of bar-shaped sensors to detect high-gradient pixels and mark them as edges in the shared memory. Later, this approach was adapted in [14] to solve the more specific image segmentation problem of concentric Strias' detection. Depending on their targets, this adaptation uses two types of agents to detect Strias. The brightening agents search for white rings, while the darkening agents search for dark rings. In this system, an agent uses three sensors to perceive its environment: one is used for positioning, and the other, disc-shaped, are used for pixel intensity discovery. The agent explores the image by following the trajectory that minimizes the addition between its two sensors during its execution. While exploring its environment (the image), the agents act directly on the image, increasing the brightness with the white ring pixels and decreasing it with the black ring pixels, which leads to the detection of Strias. The execution of the system ends when it reaches a stopping criterion.

The approach presented in [14] was extended in several ways. First, it was improved with a termination mechanism inspired by immune systems and implemented with a new multi-agent development environment called oRis [15]. Later, Guillaud et al. [16, 17] proposed a variation of this approach for the detection of growth rings from fish otoliths. In this system, the agent sensors gained a square shape instead of a disk shape to increase edge detection. The approach also uses a path map to store the detected edges instead of modifying the image. In addition, a priori knowledge in the form of shape information improves the detection rate. Then, Guillaud et al. added in [18] other improvements to their previous MAS (presented in [17]). They proposed to add thresholding of the path map to extract the first set of possible rings corresponding to the most frequented paths. The thresholded rings are then definitively validated by an inflation method similar to the active contours. Finally, the last evolution of this multi-agent approach was presented in [19]. In this last paper, all the previous work was used to improve the agent's behavior with two alternatives:

the free-agent and directed agent approaches. The first alternative uses only the gray-level information of the pixels, while the second uses the shape information. Both were evaluated on a set of 119 Otolith images for age estimation. The directed agent approach shows the best results. All the MASs listed in this paragraph have provided promising results compared to the existing methods. However, they suffer from some problems, including the constraint of Strias detection, prior knowledge, and the need for parameterization. Therefore, a separate publication has been devoted to the parameterization of the technique: [20].

Natural images were also proceeded by Melkemi et al. [21]. They presented a new approach for image segmentation based on Iterated Conditional Mode (ICM), Genetic Algorithms, and a chaotic map in the form of a MAS called CMAS. In this system, a set of segmentation agents work under the control of a coordination agent. Each agent creates a new version of the processed image during the execution using the K-means algorithm and a chaotic perturbation. Then, it segments this version using the ICM and sends the results to the coordination agent. The latter aggregates the results and chooses the best one according to an energy function. Finally, the coordinator performs a set of genetic operators on the selected segmentation and sends it as a new processed image to the segmentation agents. This process is repeated until convergence. The authors evaluated their system on a set of synthetic and real images. Thus, the experimental results demonstrate the improvement of the segmentation quality compared to the ICM segmentation alone. However, the multi-agent paradigm is used only to distribute and organize the segmentation tasks in CMAS. Therefore, there is no interaction between the population of segmentation agents, and communication is limited to an image exchange between each one of them and the coordinating agent. Moreover, this exchange is costly in terms of performance, limiting its use to small images.

Later, Melkemi and Foufou added to their approach the concept of fuzzy image representation in the form of a new MAS called FDGA-Seg [22]. They also proposed two different architectures: one centralized, the master-slave model, and one decentralized, the island model. Nevertheless, this new system inherits a high communication cost due to the amount of data exchanged between the agents (input and segmented images).

The multi-agent paradigm was also used for iris segmentation in [23]. The proposed system uses a population of agents to explore the image, searching the iris's center. The agent uses local gray-level information coupled with trained neural networks to compute its trajectory to the iris center. However, there is no interaction between the agents. Moreover, these agents are not involved in the process of iris boundary extraction. Their objective is limited to the detection of the iris center.

Multi-agent grayscale image segmentation has also been addressed using a new swarming mechanism based on the social spiders' behavior [24]. In their paper, Bourjot et al. demonstrated how bio-inspired behavior could lead to a practical approach for image segmentation. They proposed a MAS based on reactive spider agents exploring their environment and attaching silk trails for web construction. The environment represents the image to be segmented. Each pixel is drawn as a peg. Thus, the height of a peg corresponds to its gray-level value. Consequently, the spider agents evolve in this environment according to three different behaviors: movement for image exploration, silk fixation for assimilation of similar pixels, and return to the web to stay in the same region. Accordingly, an agent explores its neighborhood and fixes a silk line when encountering a similar region using thresholds for similarity tests. As a result, an extracted region corresponds to the pixels belonging to the same web at the end of the system execution. The evaluation of the proposed approach was performed on natural gray-level images and gave encouraging results. Nevertheless, the system failed to extract the targeted regions fully and requires the empirical calibration of several parameters.

The issue of segmentation of color photographic images has also been addressed through the use of MASs. An example of such a system is the one proposed by [25]. This last system, based on the work of Liu et al. [26] (detailed later in this paper), uses multi-agent diffusion, breeding, and labeling for regions detection in color images. Compared to the approach presented by Liu et al., Benyoussef et al. only introduced peer-to-peer simulation for performance optimization.

In their paper [27], Sun et al. presented a new multi-agent approach for cloud removal in sky-sea infrared images. The approach aims to detect and segment cloud areas in the image using two reactive agents: mobile agents called Search agents and a Manager agent . Thus, Search agents explore the image to segment. They search and label cloud regions' pixels using different behaviors (diffusion, breeding, marking, ...) under the control of the Manager agent. The choice of which behavior to adopt depends mainly on a set of predefined criteria (relative contrast, regional average, and standard variance of regional gray levels). The experiments illustrate the ability of the proposed system. However, the system depends excessively on prior knowledge and parameter initialization.

Multi-agent image segmentation has also been used for line detection in document images. In [28], the authors presented a system that uses a method originally developed for image resizing, namely seam carving, to extract text lines from document images using MASs. The proposed system uses a set of reactive agents to distribute the seam carving and improve the system's performance. Despite its promising results, the approach still requires the calibration of several parameters.

4.2. MAS approaches for range image segmentation

The authors of [29, 30] proposed a new MAS called 2ARIS for range image segmentation. The system includes a population of reactive mobile agents moving in an environment (the input image) and remodeling the pixels encountered during their exploration. At the beginning of the execution, the agents dispersed on the image directly start the exploration. The agents' movements are guided by a self-organization mechanism using an artificial potential field. Thus, each agent evaluates its path and detects a flat region when a sufficient number of successively visited pixels share the same properties. At this point, an agent can either align the encountered pixel that belongs to its region or modify a noise/edge pixel. Thus, an agent loses its ability to modify pixels immediately after modifying one of them and returns to its initial exploration state. This mechanism allows the smoothing of the flat regions and erasing of the noise simultaneously. In addition, alternative migrations of agents between regions result in the alignment of the boundary pixels. Therefore, experiments were performed for the segmentation of range images from the ABW database[1]. The presented results are promising and outperform some state-of-the-art approaches. However, 2ARIS suffers from several drawbacks, including parameters and thresholds requiring experimental calibration. In addition, the approach is unsuitable for segmenting images with small regions, as the latter may be considered noise and therefore erased. Furthermore, the competitive alignment of region boundaries may result in distorted and poorly localized edges.

To overcome the drawbacks listed above, Mazouzi et al. proposed several improvements to their MAS. First, a Bayesian regularization based on a new Markov Random Field (MRF) model was added to the MAS as a post-processing step in [31]. Later, the same authors proposed in [32] a variation of the 2ARIS approach called DCIS. The latter introduced the directional curvatures of the surface as a new homogeneity predicate. This variation allowed the detection of curvilinear shapes. Finally, Mazouzi et al. presented in [33] a new approach based on situated reactive agents called MABIS for the segmentation of the same type of images. MABIS is based on a cooperative region-growing method with a seed selection mechanism. Thus, shifting from mobile to situated agents has solved some problems, such as boundary distortions. Therefore, the parametrization problem remains an open question, requiring a supervised learning approach for parameter estimation.

Recently, Mazouzi and Guessoum presented a new version of their approach called CMAIS [34]. In this last MAS, the situated agents use the region-growing method for range image segmentation. In addition, CMAIS incorporates a region merging mechanism for aggregating regions with similar properties. The use of the region-growing method instead of a machine learning method eliminates any risk of overfitting. However, the approach still requires the selection of many parameters.

4.3. MAS approaches for satellite image segmentation

In [35], Liu et al. proposed a MAS for remote sensing image segmentation. The system uses cooperative detection and extraction of image intensity, texture and contour information. The segmentation process consists of three essential steps. First, three agents extract the image's intensity, texture, and contour characteristics. Then, three other agents use the extracted characteristics to segment the image using the Fuzzy C-Means (FCM) algorithm. Finally, the three resulting segmentation methods are combined to obtain a final consensus segmentation using a voting mechanism. The paper presents a visual result of an image segmentation performed using the new MAS, but no quantitative evaluation was provided. Moreover, the application of the FCM algorithm involves the use of prior knowledge. Bao et al. also proposed a variant of this MAS approach in [36]. In their MAS, they use only intensity and texture characteristics, and they also switched from the FCM algorithm to the MRF algorithm. Nevertheless, the problems inherent to the source approach remain unchanged even with these modifications.

[1] http://www.eng.usf.edu/cvprg/range/DataBase.html

MAS image segmentation has also been used in [37] for building extraction from satellite images. The authors proposed region-edge cooperation for building extraction using the multi-agent paradigm. The system achieves its objective in two different steps. First, a supervisor agent and a normalized difference vegetation index agent prepare the image for segmentation using several operations, including vegetation removal. Then, the edge and region agents use the Canny edge detector and region-growing to extract the rooftop areas in a cooperative approach, respectively. Experiments were performed on high-resolution satellite images, and the results are comparable to those of the chosen state-of-the-art method. Nevertheless, the approach requires the initialization of some prior knowledge associated with the nature of the targeted buildings in the processed satellite images.

In [38], the social-spider metaphor was used in a MAS approach for satellite image segmentation. The authors improved the initial social-spider region detection approach proposed by Bourjot et al. [24] and refined by Moussa et al. [39]. The authors added two new types of agents: a resolution agent and an edge agent. The resolution agent aims to represent the image information in different levels of a Gaussian pyramid with decreasing resolution sizes. Thus, the edge agent chooses one of these levels and applies an edge detection operator to the corresponding image. Finally, the detected edges will be used in the region detection process performed by the spider agents. The new approach correctly segmented the synthetic test image. However, it fails to detect all the regions in the satellite image. Moreover, the calibration of the parameters inherited from the social-spider metaphor remains unresolved.

4.4. Other MAS image segmentation approaches

In [40], Redjimi and Amir proposed an agent-based approach for edge detection. The system uses a hierarchical organization with a set of detector-follower agents responsible for detecting and tracking an edge at the lowest level (pixel level). Thus, the intermediate level is dedicated to partition agents, responsible for creating and managing the detector-followers in their dedicated image portion. Finally, a master agent supervises the system. The master agent divides the image into a set of parts where it creates a single partition agent. The detector-follower agents use a noise and blur estimator during the edge detection phase to select an edge detection operator suitable for the explored area. When it detects a contour using the appropriate operator, the agent follows it until it returns to its initial point. The authors tested the system on a set of different types of images, but no quantitative evaluation was provided. Moreover, there is no cooperation between the agents, and the system requires the calibration of several parameters.

Kabir et al. presented in [41] a new distributed MAS for image segmentation running in a parallel virtual machine environment for X-ray film segmentation. The authors proposed an edge-region cooperation mechanism based on a Canny edge detector and a region-growing algorithm. The system also uses other agents for preprocessing tasks and image characteristics estimation to help the segmentation agents (edge and region). Although edge-region cooperation has proven its importance for improving segmentation, many problems persist among the dependence on a pre-segmentation task for seed selection. In addition, no quantitative evaluation of the segmentation approach has been provided.

5. Multi-agent medical image segmentation

Since the 1990s, the multi-agent community has been addressing the issue of medical image segmentation to overcome some of the drawbacks of conventional segmentation algorithms. Several agent-based systems have been published for the segmentation of different types of medical images. This section reviews and categorizes these MASs based on the segmentation method(s) they use.

5.1. Classification-based approaches

Classification methods have been widely used with the multi-agent paradigm for medical image segmentation. Since these methods involve dividing the image pixels into several categories, they are well suited for dividing the tasks among a population of agents where each agent segments its portion of the image. Probabilistic methods were one of the possible directions studied in multi-agent image segmentation by classification.

Probabilistic methods have been explored for the design of classification-based multi-agent medical image segmentation systems. Scherrer et al. proposed in [42, 43, 44] a new distributed and localized implementation of the MRF algorithm for the segmentation of brain MR images. The so-called LOCUS-T system performs image segmentation according to two layers of information: tissue information and structure information. For tissue segmentation,

Table 1: A literature review of multi-agent approaches for image segmentation of several types of images.

Approaches	Year	Segmentation Method	Processed Images
Ballet et al. [12, 13, 14]	1997	Edge detection (mobile agents and gradient calculation)	Syntetic and natural gray scale images
Kagawa et al. [11]	1999	Bio-inspired (mobile agents and pheromones)	Photographic images
Guillaud et al. [16, 17]	1999	Edge detection (mobile agents and gradient calculation) and shape detection	Photographic images
Guillaud et al. [18]	2002	Edge detection (mobile agents and gradient calculation) and thresholding	Photographic images
Kabir et al. [41]	2002	Region growing and contours detection	Synthetic and photographical images
Rodin et al. [19]	2003	Edge detection (mobile agents and gradient calculation)	Photographic images
Bourjot et al. [24]	2003	Bio-inspired image region detection (Spyder agents)	Photographic images
Melkemi et al. [21]	2005	ICMs, genetique algorithms and chaotic map	Synthetic and photographic images
Mazouzi et al. [29, 30]	2007	region smoothing using mobile agent affected by an artificial potential field	Range images
Labati et al. [23]	2009	Gradient estimation, thresholding, and neural networks	Photographic images
Mazouzi et al. [32]	2009	region smoothing using mobile agent, MRF, and ICM	Range images
Melkemi et al. [22]	2010	ICMs, genetic algorithms, chaotic map, and fuzzy image representation	Synthetic and photographic images
Mazouzi et al. [33]	2011	Region growing and parameters estimation	Range images
Benyoussef et al. [25]	2011	Multi-agent diffusion, breeding, and labelling	Photographic color images
Sellaouti et al. [37]	2012	Morphological dillatation, Canny edge detector, region growing	Satellite images
Redjimi et al. [40]	2012	Adaptative edge detection using mobile agents	Photographic images and MR images
Bidi et al. [38]	2013	Bio-inspired image region detection (Spyder agents)	Synthetic and Satellite images
Liu et al. [35]	2017	Thresholding, texture detection using correlation matrix, Canny edge detector, and fuzzy classification models	Satellite images
Bao et al. [36]	2017	Thresholding, texture detection using correlation matrix, Canny edge detector, MRF	Satellite image (sensing images)
Daldali and Souhar [28]	2018	Multi-agent seam carving	Photographic images
Sun et al. [27]	2019	Similarity detection (gray-level information)	Photographic images

a global tissue agent divides the image to be segmented into a set of non-overlapping cubic volumes. These volumes are then assigned to a set of local tissue agents. The global agent also provides an initial model for these agents. Thus, they aim to distribute their assigned voxels over the possible tissue categories. In addition to the local tissue agents, LOCUS-T uses a second population of structure agents to detect subcortical structures within the processed image through MRF. These structure agents are used to distinguish structure voxels from the rest of the image. Thus, a local tissue agent cooperates with its neighbors and structure agents to correct its local MRF model. This behavior produces a cooperative process where the model parameters are iteratively optimized. To evaluate their approach, the authors tested LOCUS-T on two different brain MRI datasets, namely the BrainWeb phantoms database from the McConnell Brain Imaging Centre [2] [45] and the Internet Brain Segmentation Repository (IBSR) of Harvard Laboratory [3]. The experimental results presented highlighted the efficiency of LOCUS-T in terms of segmentation quality and execution time. However, the main drawback of this MAS approach is its dependence on prior knowledge and the need for parameter estimation. The latter was addressed in [46], where a third spatial MRF improves the estimation of local parameters based on the intensity distribution. This upgrade provides the new MAS, called FBM-TS, with better robustness against the intensity non-uniformity artifact. Unfortunately, this improvement concerns only a subset of the needed parameters.

Another method based on multi-agent classification used for the segmentation of medical images is thresholding. Thus, Chitsaz et al. [47] proposed in their paper an approach where the set of agents is composed of a moderator agent and several local agents in charge of the system's management and the classification and labeling of the pixels, respectively. Thus, the moderator agent creates and initializes the local agents, assigning them portions of the images. Each agent then labels the pixels in its assigned portion according to the minimum and maximum extreme thresholds. The thresholds and the number of classes are defined using prior knowledge. The experiments performed on a set of five CT images provide satisfactory accuracy results. However, the system relies mainly on prior knowledge. In addition, the disadvantage of thresholding techniques is the exclusion of spatial pixel information. Finally, only a few interactions exist between the agents. Therefore, the approach can be considered as a simple parallel thresholding segmentation.

To overcome the problem of determining thresholds, Chitsaz et al. introduced the use of reinforcement learning in [48, 49]. Using a training dataset, agents learn to estimate the best thresholds for image segmentation. Then, they use this acquired ability when processing the parts of the image assigned to them. The experimental results presented illustrate improvements in terms of segmentation quality. Nevertheless, the number of targeted classes must be defined manually and remains limited to the segmentation of the type of images used during the learning process.

Benchara et al. presented in [50] a parallel agent-based system for brain MR image segmentation. The system adopts a hierarchical organization where a team leader agent manages mobile team worker agents. During the segmentation process, the team leader initializes the worker agents and assigns a subpart of the input image to each of them. Thus, the worker agents in the team begin the segmentation of their sub-image using the Type-2 Fuzzy Clustering Algorithm (T2FCA) [51]. Thus, the team leader agent collects all the results, evaluates the convergence of the process, distributes a new set of class centroids to the worker agents of the team, and launches a new clustering cycle. This process is repeated iteratively until the system converges. The paper presents some experimental results with the segmentation of a brain MR image with tumor tissue. These visual results demonstrate the system's capabilities for segmenting this type of image. However, the use of T2FCA implies some drawbacks, starting with the initialization of the class centroids. Moreover, no interaction has been included between the agents of the work team, making the system appear as a simple parallelization of this algorithm.

Later, a different version of this approach, where the C-Means algorithm replaced the T2FCA, was presented in [52]. Thus, replacing one clustering algorithm with another may affect the results' quality, but the approach's problems remain the same. Similarly, the algorithm FCM has also been integrated into an improved version of this MAS approach in [53]. However, the improvements, including adding a new third type of agent, only concern the distribution and management of work.

In MAS-based medical image segmentation using classification, we can also find approaches based on machine learning. According such an approach a recent work is presented in [54]. This paper proposes the use of MASs with machine learning to segment knee articular cartilage in MR images. The approach employs three kinds of agents, each dedicated to a type of cartilage tissue, for the 3D MRI segmentation of the knee. During the system's execution, each agent uses a machine learning classifier to label the knee articular cartilage's corresponding region of interest. Then, the results are combined using a region of interest fusion layer. A backpropagation mechanism was also used to allow joint learning of shape and spatial constraints. For its experimental evaluation, the proposed system processed a set of

[2](https://brainweb.bic.mni.mcgill.ca/brainweb/)
[3](https://www.cma.mgh.harvard.edu/ibsr/)

176 3D knee MR images from the iMorphics dataset of the OAI database [4]. Thus, this evaluation showed impressive segmentation results but failed to compare them with other state-of-the-art segmentation techniques. Furthermore, no interaction occurs during the segmentation process between the three agents.

Machine learning was also used in [55] for medical image segmentation. In their paper, Liao et al. proposed a new method called "iteratively-refined interactive 3D medical image segmentation via Multi-agent reinforcement Learning (IteR-MRL)". In conjunction with user interactions, this method uses the multi-agent reinforcement learning mechanism to iteratively refine a coarse segmentation produced by an initial segmentation method. Each agent represents a voxel in this system, trying to find its most appropriate label with a particular probability. Thus, the agent learns to adjust its label based on the previous segmentation, the user's correction (called hints), and a reward/punishment mechanism. The authors tested their method on several 3D MR image data sets to evaluate its effectiveness. Thus, the segmentation results illustrate the performance of the proposed approach compared to some state-of-the-art segmentation methods. However, IteR-MRL suffers from problems common to machine learning methods, such as the need for a set of manually segmented images during the learning phase as ground truth.

5.2. Edge-based approaches

In this category, agents generally explore the input image, looking for discontinuities in the pixel intensity function. This search process induces edge detection and, thus, image segmentation. Many MAS-based approaches use edge detection for medical image segmentation. Some of them are listed below.

In their paper, Spinu et al. [56] presented a multi-agent edge detection system based on two phases (an analysis phase and a processing phase) for medical image segmentation of MR images. The MAS divides the image into distinct areas based on noise and texture information during the analysis phase, producing a global characteristic map. Then, agents use this map to adapt filtering and edge detection operations on each individually identified area during the processing phase. Finally, an evaluation process measures the segmentation's quality and the processing's efficiency. The agents adjust and repeat the filtering and edge detection operations based on this evaluation to improve image segmentation. The system stops when it reaches a convergence criterion. The proposed approach was tested on a noisy heart MR image, and only the initial visual results were presented for the evaluation of the edge detection efficiency. The paper presented a promising, fully parallel approach; however, several parameters required calibration, and no quantitative results were presented. In addition, the experiments were conducted only on a single MR image.

In [57], Spinu et al. incorporated the use of error minimization into their system. The presented approach introduced a new expression for the estimation of the edge detection error. Therefore, they incorporated this estimate into the evaluation phase presented in [56]. The authors also added to the initial MAS the possibility of dividing an initial area into sub-zones to improve edge detection. The improved approach was therefore tested on only two images (a heart MR image and an image of muscle cells). Moreover, the effectiveness of [56], and [57] cannot be compared since they only use visual results for their evaluations.

Another integration of edge detection for MAS-based medical image segmentation is the one proposed in [58], where the authors presented a new approach for processing medical image sequences. The proposed system uses the active contour method for edge detection, where the agents represent the points composing a curve. Thus, the mobile reactive agents move in the image to meet the targeted edges according to an energy minimization process. Each set of detected edges is then used to initialize the agents for the next image in the sequence. Experiments were performed on sequences of biological cell and echocardiographic images using a NetLogo[5] implementation. The paper illustrates the effectiveness of this MAS with a set of visual results of detected edges. However, the approach remains semi-automatic, requiring user intervention for curve initialization and parameter calibration. Furthermore, the approach fails to detect edges when dealing with images containing artifacts.

Later, Fekir and Benamran proposed in [59] an improved version of their previous approach. This improved version describes a pyramidal architecture of subsystems, where each pyramid level represents an instance of the previous MAS (described in [58]). This architecture aims to provide multi-resolution edge detection. Thus, the high levels of the pyramid operate at low resolution, and the resolution increases when going down to the lower levels. Experimental results demonstrate the efficiency of this approach compared to classical edge detectors (Canny and Sobel). Nevertheless, the drawbacks mentioned in the authors' previous MAS remain unresolved.

[4]https://nda.nih.gov/oai

[5]NetLogo is a multi-agent programmable modeling environment. For more details, see https://ccl.northwestern.edu/netlogo/

Nachour et al. presented in [60] a MAS approach for edge detection based on the minimization of an energy function, according to a vector field convolution [61]. The system uses four agents: scout agents, edge agents, node agents, and observer agents. The scout agents explore their environment (the input image), looking for neighboring pixels that minimize the energy function of the vector field convolution. When they encounter local energy minima, the scouts lunch their edge agents. Thus, the mission of the edge agents is to follow the contours on which the scouts created them until their closing. When an edge agent cannot close its contour, it negotiates with the neighboring edge agents for contour merge. Furthermore, a scout agent lunches a node agent instead of an edge agent when it encounters a minimum with multiple contour directions to follow. This node agent will create the edge agents needed to follow all possible directions. Thus, an observer agent controls the system by creating and initializing agents when necessary. This MAS approach was implemented on the JADE platform[6], and experiments were performed on synthetic and medical images. According to the paper, the approach provided a more efficient edge detection than that obtained using the gradient vector flow method. However, the proposed MAS requires the use of several parameters and thresholds.

In another paper [62], the same authors used energy minimization with an active contour model in the form of a multi-agent fuzzy approach for edge detection. The presented work describes an approach where each agent controls the movements and deformation of the contour it manages based on a fuzzy membership function. The latter function evaluates the membership of a pixel to an edge according to the histogram of the image and some predefined thresholds. The experimental results illustrate the robustness of noise compared to a simple fuzzy energy-based active contour algorithm, even when processing medical images. Nevertheless, the published paper omitted the integration strategy of the MAS paradigm. Therefore, neither the behavior nor the interactions of the agents were described.

5.3. Region-based approaches

Region-based MASs for medical image segmentation rely on similarity to aggregate all pixels belonging to the same region. This aggregation can be performed on individual pixels as in the case of region growing. It can also be performed on blocks of pixels using the region merging method. The following paragraphs review some of the region-based MASs methods for medical image segmentation.

Mobile reactive agents were used by Liu et al. [26] for image segmentation based on a region detection approach. In the proposed MAS, the reactive mobile agents use a similarity predicate to detect homogeneous image areas according to three behaviors (diffusion, breeding, and labeling). First, an agent uses diffusion behavior to explore its environment (the image), looking for a homogeneous region. Then, breeding behavior starts when the agent encounters a pixel that satisfies its homogeneity predicate. The homogeneity predicate used, based on the contrast, the region mean, and the standard deviation triggers the pixel labeling and breeding behavior successively. Thus, the breeding behavior consists in creating a set of offspring agents in the neighborhood of the parent agent. These offspring agents will either label their position as a homogeneous segment or start a diffusion behavior. The authors presented a visual result of brain MR image segmentation in their paper, where four different regions were correctly segmented. However, the system needs a lot of initialization information, such as the number of the targeted region and their properties (used to set the parameters of the similarity predicate).

Region growing was also the base method for the segmentation of brain MR images in [63]. The latter paper presents a system dedicated to detecting white matter, gray matter, and cerebrospinal fluid based on using three types of local situated agents: global and local control agents and tissue-dedicated agents. The system performs image segmentation in two phases: model estimation and voxel labeling. First, the local control agents compute the radiometric model using an estimation maximization algorithm. Before validating a model, a local control agent must compare it with the models of neighboring agents. This cooperation provides an excellent mechanism for proper radiometric model determination. Then, the tissue agents perform the region-growing pixels labeling using the models obtained from the previous phase. The global control agent manages the creation of all other agents. It also manages their assignment to a subpart of the image to be segmented. To evaluate the efficiency of their approach, the authors performed a set of experiments on images from the Brainweb phantom image dataset [45] (see note 2). The results demonstrate the robustness of the proposed approach to noise and intensity non-uniformity artifacts. However, the approach requires the calibration of several parameters.

[6]JAVA Agent DEvelopment Framework is an open-source platform for peer-to-peer agent based applications. For more details, see https://jade.tilab.com/

Another application of the agent-based paradigm with region-based segmentation is the one presented in [64]. This paper, authored by Benamrane et al., proposed a MAS for medical image segmentation. Thus, the presented approach uses a cooperative region expansion strategy based on region growth, merging, and agent interactions. First, a global agent initializes the system by launching a region agent set in the environment (the input image). Then, each agent begins to expand its region by assimilating neighboring pixels that satisfy its similarity predicate. When the initial segmentation is generated, the region agents start an interaction process using FIPA protocols[7] to select the best possible merging plan. This merging phase is divided into two steps, differentiated by their distinct merging predicates. The approach, implemented using the JADE platform(see note 6 for more details), was experimented on brain images MR from the Harvard Medical School dataset[8]. A visual evaluation of the presented segmentation results suggests a satisfactory efficiency in comparison with the Canny edge detection algorithm [65]. However, the predicates used are based on a set of parameters that require empirical estimation.

Fleureau et al. [66] also used situated agents in conjunction with a region detection approach for medical image segmentation. In their paper, the authors proposed a new MAS for the segmentation of heart structures in 3D cardiac scanner images. This system uses a hierarchical organization based on a set of worker agents managed by a controller agent. Thus, the user manually positions the worker agents in the image to be processed. Then, their goal is to detect and assimilate the voxels corresponding to the region assigned to them using a region-growing algorithm. Thus, these agents use during the growing process an assimilation predicate computed through a learning phase. Therefore, the worker agents select the voxels they want to assimilate, but the controller agent must perform the assimilation. This mechanism aims at coordinating the cooperation and competition between the agents. Consequently, the controller uses the distance between a worker positioned on a pixel to be assimilated and the seed in its region to manage conflicts. Thus, a voxel selected by different workers will be assigned to the one with the lowest distance. The presented experiments illustrate the approach's effectiveness when segmenting heart scan images from different datasets. However, it still relies on user intervention for the initialization of region seeds. In addition, the paper imprecisely describes the assimilation predicate and how to perform its calibration.

Another MAS region-based MR image segmentation approach was proposed by Bennai et al. in [67]. The approach is based on the proliferation of several generations of reactive mobile agents, operating and interacting on an input image to perform its segmentation. Thus, the agents use a two-phase region growing mechanism, and an agent region merging step to extract homogeneous regions from the rest of the image. The first phase employs a random walk mechanism to extract the characteristics of the image. In contrast, the second one uses the latter in a region-growing algorithm to detect the regions of interest. Lastly, a border refining method and a noise removal mechanism are used to complete the detected regions. The proposed approach was tested with the BrainWeb dataset (see note 2) for white and gray matter detection. The experimental results are promising. However, the approach still needs parameters' calibration. Moreover, the final results depend on the initial random distribution of the mobile agents on the image.

5.4. Regions-edges cooperation-based approaches

The multi-agent paradigm offers the possibility of combining several segmentation methods within the same approach. This advantage is particularly suitable for combining edge and region detection techniques. Thus, several approaches published in the literature have tried to use this advantage for medical image segmentation. Among them are the ones described in this subsection.

In [68], the authors proposed a new cooperative approach for brain MR image segmentation. The system is divided into three parts: a deformable model, an edge detector, and a MAS, working together to achieve the segmentation of the brain tissues in MR images. The MAS is in charge of the main segmentation task. Thus, the deformable model and the edge detector provide support through integrative, augmentative, and confrontational cooperation. Thus, the segmentation process is divided into three main phases: specialization, where the deformable model initializes the agents inside the regions of interest; the merging of information, where edge agents combine information provided by the deformable model and the edge detector for borders refining; and finally the retro-action over slices, where the segmentation results replace the deformable model when initiating the segmentation process for the adjacent slices.

[7]FIPA is a standards organization for agent-based technology. More details can be found on http://www.fipa.org/

[8]http://www.med.harvard.edu/AANLIB/home.html

The proposed MAS was tested on a set of brain MRI slices and achieved an average segmentation quality of 96%. The authors also demonstrated that the use of cooperation significantly improved this quality. However, the system relies excessively on prior knowledge and requires the initialization of several parameters.

Similarly, Porquet et al. [69] proposed a region-edge cooperative framework dedicated to image segmentation and applied it to MR images. The presented MAS platform aims at providing a simple and easy way to implement region-contour cooperation in image segmentation. The agent behavior, represented by an automata, manages the actions performed during execution. This behavior mainly consists in merging and splitting regions from two initial segmentations: region detection using a quadtree [70], and edge detection using the Deriche edge detector [71]. Therefore, agents can be either region agents or edge agents in this system. Thus, their willingness to merge or split is related to a set of threshold-based predicates. Thus, the presented visual segmentation results illustrate the effectiveness of the proposed MAS approach when processing a brain 2D MR image. These results are promising, considering that the approach avoids the use of any prior knowledge. However, the system's performance depends on the initial segmentation and the experimental parameterization of several thresholds.

In [72], a MAS combining the Canny edge detector and the region-growing algorithm addressed the challenge of mammography image segmentation. The system relies on the two previously cited algorithms to achieve initial edge detection and initial region determination. After initialization, the proposed MAS uses two graphs to merge the regions and edges of the image iteratively. Thus, this iterative MAS edge-region cooperative segmentation is implemented as an irregular pyramid. The pyramid consists of a set of levels representing the image to be segmented with decreasing resolutions. Two populations of agents (region and edge agents) start interacting and cooperating to improve the initial segmentation through several behaviors. The proposed approach is interesting, but the paper omitted the merging conditions and the agents' interaction mechanisms. Moreover, no quantitative segmentation results were provided.

Another form of cooperation used in MAS systems is the sequential region-edge cooperation proposed by Pereira et al. [73]. In their paper, the authors proposed an approach based on a two-phase segmentation of microaneurysms in fundus images. The first step of this segmentation consists of a preprocess applied to the image using a set of filters. This preprocess aims to isolate vessels and microaneurysms from the image background. Then, the second step is devoted to the segmentation and detection of microaneurysms in the filtered image. This last image represents the environment where two kinds of agents evolve. First, the exploration agents perform edge tracking and detection of regions of interest. Then, each exploration agent launches a region agent when it encounters a region of interest during its exploration. Then, the region agent starts a region-growing operation to segment the microaneurysm at its position. During the region-growing process, two or several region agents can merge if necessary. To evaluate their approach, the authors performed experiments on two different datasets[9,10]. The results show that the proposed approach provides a microaneurysm detection rate comparable to that of state-of-the-art methods. However, the system remains sensitive to noise despite filtering during the preprocessing phase. In addition, the proposed approach relies on the experimental determination of several thresholds.

In another context, Nachour et al. presented in [74, 75] a multi-agent 3D reconstruction of the human femur in MR images. Since the 3D CAD model reconstruction process requires extracting the targeted area from the rest of the image, the authors proposed a new MAS segmentation approach dedicated to this purpose. Thus, the system uses three kinds of reactive agents: a controller for system initialization, region agents for region detection, and edge agents for contours detection. Thus, the region agents segment the image using a seeded region-growing algorithm with a similarity predicate based on gray-level and gradient information. Therefore, seed initialization relies on a thresholding process. Furthermore, when an agent completes the process of growing its region, the controller agent creates an edge agent to delineate the contours of the detected region. The system was implemented in JADE (see note 6 for more details) and tested on a femur MR image. The segmentation results were sufficient for the generation of a 3D model. However, the system requires calibration of several parameters, user intervention before the 3D reconstruction, and thresholding preprocessing.

In [76], Allioui et al. proposed a multi-agent platform for image segmentation based on the cooperative use of several segmentation methods. The system is divided into three parts: the data part containing the image to be processed, the knowledge part encapsulating the segmentation methods and the prior knowledge, and the active part containing

[9] https://www.adcis.net/fr/logiciels-tiers/messidor-fr/

[10] http://webeye.ophth.uiowa.edu/ROC/

all the agents. The latter includes three kinds of cognitive agents: a supervisor agent, analysis agents, and segmentation agents. Thus, the supervisor agent manages the analysis agents' creation, interactions, and communication, one analysis agent for each slice of the volume. Consequently, the analysis agent extracts information from its slice to generate and initialize a set of segmentation agents. Thus, the segmentation agents (region or contour agents) use prior knowledge to choose the best segmentation method based on the parameters provided by their analysis agent's work. The system was tested on an abdominal CT volume. The visual results suggest satisfactory tissue extraction. However, the analysis criteria and segmentation predicates were omitted in selecting the segmentation method. Furthermore, the same authors presented in a recent paper [77] a more detailed and improved version of the reviewed MAS with a description of the region-growing segmentation procedure. The paper also provides a quantitative evaluation of the segmentation results.

In [78], multi-agent systems were also used to combine contours' detection with regions' detection for the segmentation of medical images. The proposed approach, called MLISS (Multi-Local Image Segmentation System), relies on a segmentation process divided into two steps: the detection of discontinuities step and the detection of similarities step. During the first step, a population of reactive situated agents, homogeneously distributed on the image to segment, uses a K-means algorithm to detect the contour pixels according to their gradient values. During the second phase, another generation of agents employs the resulting categorization to detect the final regions using a combination of region-growing and region merge. Authors conducted experimentation on the images provided in the BrainWeb dataset (see note 2). The systems provided significant stable results for brain white matter detection despite the increase of two artifacts: noise and intensity non-uniformity (INU). However, the proposed system suffers from limitations when dealing with narrow regions.

Lastly, Bennai et al. [79] proposed a new stochastic multi-agent approach for medical image segmentation used for tumor detection in brain 3D MR images. The system, named MAMES (Multi-Agent approach For MEdical image Segmentation), combines the benefits of the K-means border pixels detection proposed in [78] with the two-phase region detection presented earlier in [67] for 3D brain image segmentation. Thus, the proposed approach was tested for brain tumor detection using the BraTS dataset (BraTS2018[11]) [80]. The system was able to correctly extract the tumoral region using only one image modality, whereas most existing systems use the four provided modalities. Furthermore, the proposed system does not require any prior knowledge. However, it still needs the experimental calibration of a few parameters.

5.5. Mixed Methods

MASs are not limited to the combination of region and edge detection methods. They offer the possibility to include two or more heterogeneous methods in a MAS approach. This combination's main objective is to eliminate each method's drawbacks by using cooperation. Among these kinds of medical image segmentation MASs, we can find the approaches detailed below.

First, in [81], then in [82], Boucher et al. proposed a MAS approach based on specialized cognitive agents for the segmentation of living cells in an image sequence. In the presented system, five different sets of agents (the nucleus, the white halos circle, the crests, the pseudo-pods, and the background) interact under the control of a schedular. The system organization assigns a specific part of the image to each type of agent to be segmented. Moreover, the creation of the agents follows a particular plan. First, a schedular creates the nucleus agents according to a set of parameters. Then, the nucleus agents generate the background and the crests agents. Finally, the pseudo-pod and white halo agents are the last sets of agents to be launched into the image. After initialization, each of these agents uses three different behaviors during the execution of the segmentation process, namely the perception behavior for pixel assimilation (adaptive thresholding, region growing, and edge following), the interaction behavior (merging and negotiation), and the breeding behavior. The proposed MAS performed segmentation tests on two types of living cell images. As a result, a visual evaluation of the segmentations was provided, but no quantifiable evaluation metrics were used. In addition, the MAS presented is too specific since it uses prior knowledge of the images to be segmented. It also requires the calibration of a large set of parameters.

Based on a stack of graphs with decreasing cardinality, called a pyramid, Duchesnay et al. [83] proposed a new MAS architecture for image segmentation and interpretation. A graph, designed as a set of linked agents, describes a

[11] https://www.med.upenn.edu/sbia/brats2018/data.html

possible image partition at each pyramid level. Each node (agent) is associated with a region of the image. Therefore, the links between the nodes represent the physical proximity between the regions. The first layer of the pyramid results from the use of a split algorithm. Thus, the segmentation process iteratively performs a cooperative merging procedure. The agents elect the survivors of the next level at each iteration based on the characteristics of their region and the affinity criterion. Depending on the selected characteristics, the election may involve the use of prior knowledge. Then, the survivors impose their merging plan and become the nodes of the next pyramid layer. The presented paper illustrates the effectiveness of the proposed MAS architecture with visual results of synthetic image segmentation. Therefore, no qualitative evaluation was provided.

Later, the same architecture was used in [84] for the implementation of distributed MAS with some improvements. In this improved system, the initial breast CT image is processed using both region and edge information simultaneously. As a result, a new type of agent, edge agents, has been added to improve the robustness of the approach. Thus, edge agents are generated in the first layer using a sequence of edge detection procedures, while region agents remain generated using a quadtree algorithm. During the execution of the system, the population of edge agents remains unchanged. Their goal is, therefore, to cooperate with the region agents to optimize the region merging plan. Since the architecture is suitable for parallel implementation on a group of computers, it requires a manager agent. This agent is responsible for the organization and communication between the other agents. In addition, the MAS uses two algorithms to manage the exchange of messages. The evaluation of the approach performed on a mammography X-ray image with a tumor area did not yield qualitative results. Moreover, in addition to the parameterization required for characteristic extraction and affinity calculation, the major drawback of this architecture is the dependence of its results on the initial segmentation methods used to generate the first layer of the graph. Finally, a more detailed approach description was presented in [85] with an exhaustive characterization of the edge-region cooperation.

In [86], Haroun et al. presented a MAS called MMAS for brain MR image segmentation. The system combines the FCM algorithm with region growing to divide a 2D brain MR image into the three main brain tissues (white matter, gray matter, and cerebrospinal fluid). The segmentation process takes place in three phases: the initialization phase, where the global agent launches a set of region agents on the image; the region growing phase, where the agents aggregate pixels of the same characteristics; and the negotiation phase, where the agents interact to perform the merging of their regions when it is possible. Thus, the presented MAS combines the FCM and the region growing algorithm for two tasks: seed selection and assimilation predicate evaluation. An agent only assimilates a pixel during the growing process if it satisfies a region's similarity predicate regarding gray-level intensity. The pixel should also have a membership value higher than a fixed threshold.

Furthermore, they negotiate for a possible merge when two regions are adjacent. The segmentation stops when no assimilation or no merge is possible. The paper presented visual results with MR image that demonstrate the improvements brought by MMAS compared to the use of FCM alone. However, MMAS suffers from the need for parameterization issues. Both seed selection and pixel assimilation require thresholds. We assume that this is also the case for the merge predicate since the paper omits the details of the merging procedure. In addition, MMAS also needs prior knowledge in the form of the number of classes to be detected.

FCM was also used along with deformable models in an edge detection MAS [87]. The presented MAS aims to segment anatomical structures inside brain MR images. Accordingly, each agent manages a medial representation (m-rep) deformable model, intending to shape its segment according to the anatomical structure present in the image. The agents are cognitive and base their behaviors on a prior knowledge set, including a tissue segmentation performed using the FCM clustering algorithm. These cognitive agents move their models led by their sensors, beliefs, and motivation to enclose the brain structures during the segmentation process. Experiments were conducted on a set of brain MR images provided in the IBSR dataset (see note 3). The presented results are comparable to those of a human expert. However, the system relies excessively on prior knowledge and employs a set of parameters that must be set empirically. Besides, the final results are strongly dependent on the model's initialization.

Cognitive agents were also used with medical images in [88, 89]. In the latter paper, Bovenkamp et al. presented a MASs dedicated to the segmentation and interpretation of intravascular ultrasound images. Inside this MAS, each cognitive agent is responsible for detecting one sort of image object according to its knowledge and goals. Therefore, an agent uses its corresponding high-level knowledge to control the segmentation process. This control consists of selecting an appropriate segmentation procedure that may involve one or more segmentation algorithms. Thus, the interactions of the agents improve the efficiency of the segmentation and interpretation process. Experiments were performed on a set of intravascular ultrasound images using the presented system implementation. Six types of agents were developed in this implementation to extract the tissue in the image (lumen, vessel, calcified plaque, shadow, and side branch). The results presented were comparable to the ones of some state-of-the-art approaches. However, based on high-level knowledge, the system architecture is difficult to scale. Detecting a new type of object requires the design of a new agent with corresponding control rules. Later, Bovenkamp et al. evolved their approach in [90] by introducing a user-agent interaction mechanism. This improvement increased the quality of the segmentation but did not solve the inflexibility problem.

Bio-inspired multi-agent approaches are also able to integrate several algorithms for medical image segmentation. In [91], Moussa et al. presented two different bio-inspired methods: the first one, based on ant colonies, aims at detecting edges, while the second one, consisting of an optimized version of the work of Bourjot et al. [24] (described previously), deals with regions. Hence, the social ants' approach uses mobile reactive agents to explore the image using pheromones and mark the pixels whose gradient value is above a predefined threshold.

On the other hand, the social-spiders approach detects regions as described previously when explaining the approach presented in [24], but with automatic calibration of the gray-level thresholds. Experiments were performed on 2D synthetic and head CT images, with and without artificial noise. The results suggest the effectiveness of the social-ants approach for edge detection on clear images, while the spider-based approach provides better robustness to noise. Nevertheless, both approaches require the manual initialization of several thresholds.

Subsequently, the social-spiders approach has been improved. In [92], the image histogram was used to detect the intensity information in the image to initialize the assimilation thresholds. Then in [39], a stopping mechanism was added as well as a 3D implementation. This new implementation showed encouraging results when processing images from the BrainWeb dataset [45] (see note 2). However, it still suffers from over-segmentation and requires long processing time.

Recently, Allioui et al. proposed in [93] a MAS for medical image segmentation using a negotiation strategy based on game theory. The system first uses super-pixel segmentation to generate a set of regions. These regions are then integrated into a region adjacency graph, where each node representing a region is assigned to an agent. Then, the system runs a merging process to extract the final regions. Thus, the agents start negotiating to develop a merge plan. This negotiation uses game theory to concatenate similar regions using predefined criteria. Experiments performed on a knee volume, a shoulder, and an abdomen MR images, extracted from the PCIR dataset[12], illustrate satisfactory results compared to state-of-the-art methods. However, this approach suffers from its dependence on the initial super-pixel segmentation. In addition, the merging procedure depends on the calibration of several thresholds.

More recently, Allioui et al. integrated the use of the super-pixels method for the seed selection inside their MAS previously presented in [94]. Developed for Alzheimer's disease detection, it was designed as a new MAS segmentation platform [95]. Experiments with this new MAS have demonstrated its effectiveness for Alzheimer's disease detection compared to well-known segmentation approaches. However, in addition to the problems inherited from the authors' previous MAS (see [93]), the new system requires a set of preprocessing that can affect the segmentation results.

Finally, the authors presented in [96] a new MAS for the segmentation of the 2D medical images. This approach combines region-growing with Particle Swarm Optimization (PSO) to reach a common agreement or consensus state between agents, to improve segmentation results. Using goal-based agents, the new approach yielded better results than those provided without PSO when processing the SOFTENTA medical imaging demonstration dataset[13]. Nevertheless, this architecture still depends on the determination of several parameters.

6. Discussion

In the last decades, many original approaches based on MASs have addressed the problem of medical image segmentation. One strategy adopted by some of these approaches is to improve an existing classical segmentation method by resorting to the multi-agent paradigm. This scheme is thus employed with MAS approaches based on classification, region detection, and edge detection. On the other hand, some proposed approaches are based on combining several segmentation methods to integrate the advantages of the involved methods and overcome their

[12]http://www.pcir.org/index.html
[13]https://demo.softneta.com/search.html

drawbacks. In this category of approaches, we find those that use the similarity and discontinuity properties of the image to ensure the best possible segmentation. These approaches (region-edge cooperation) are usually based on a cooperative implementation of a region detection algorithm with an edge detection operator. This form of cooperation offers many efficiency improvements but also increases the MASâĂŹs complexity.

In contrast to MAS segmentation architectures limited to using two detection methods, some approaches proceed by encapsulating several different methods. These mixed methods MAS approaches can simultaneously use their different detection methods or choose the preferred one based on a selection procedure. Therefore, this categorization of MAS medical image segmentation methods is detailed in Table 2.

In line with the review of different MAS approaches for medical image segmentation presented in this survey, Table 3 and Fig. 1 summarize the characteristics of these MASs according to our proposed categorization. Moreover, Fig. 2 illustrates the distribution of these characteristics among all the examined MASs. Thus, it highlights the preponderance of reactive architectures over cognitive ones for the segmentation task, especially for low-level tasks. This preponderance is consistent with the use of high-granularity MASs. Since reactive agents generally incorporate simple behaviors, low-granularity MASs offer the possibility to employ them widely without negatively impacting system performance. In contrast, cognitive agents work primarily on complex or high-level tasks, such as algorithm selection. Because of the processing power they consume, cognitive agents typically operate in MASs with high granularity.

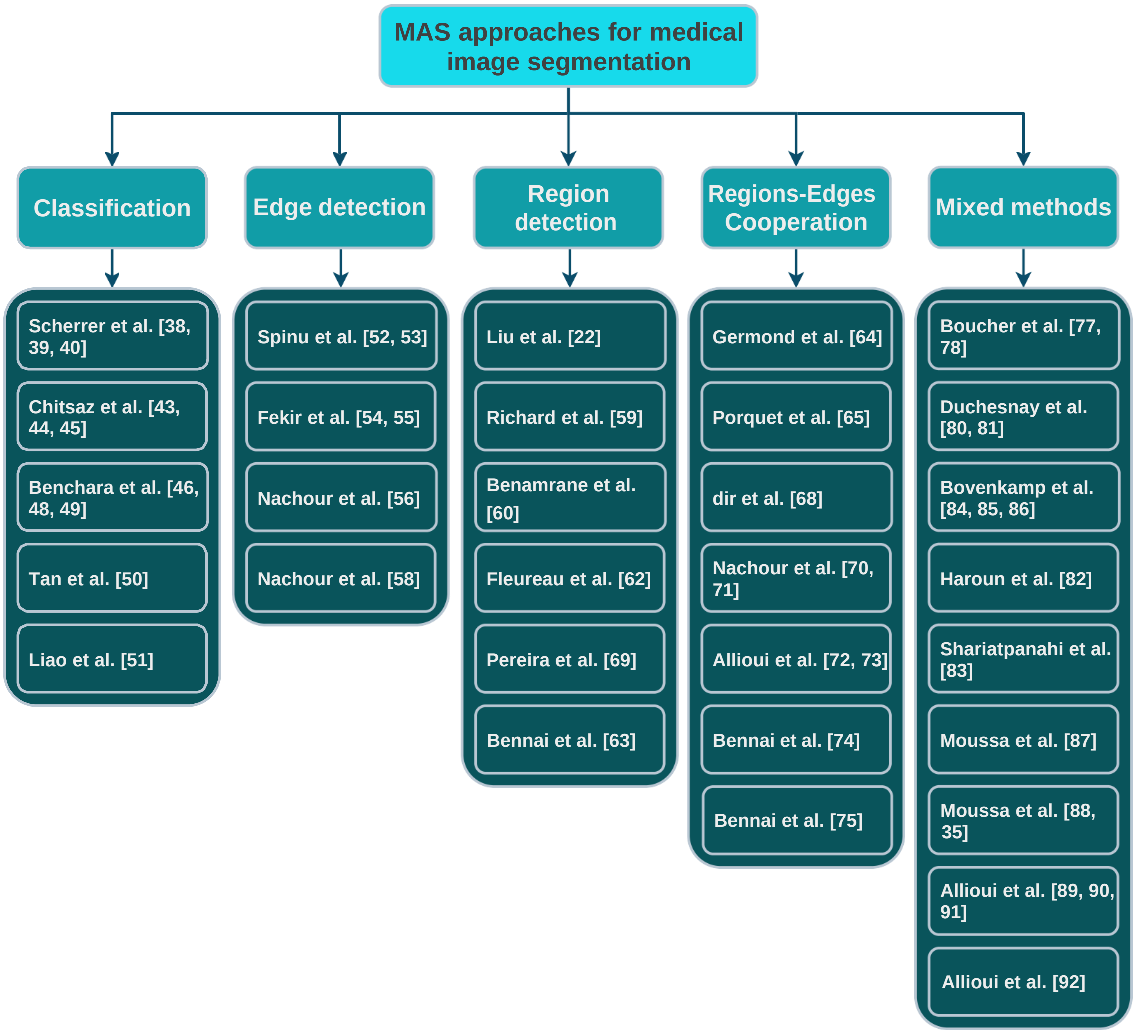


Fig. 1: Categorization of multi-agent medical image segmentation approaches

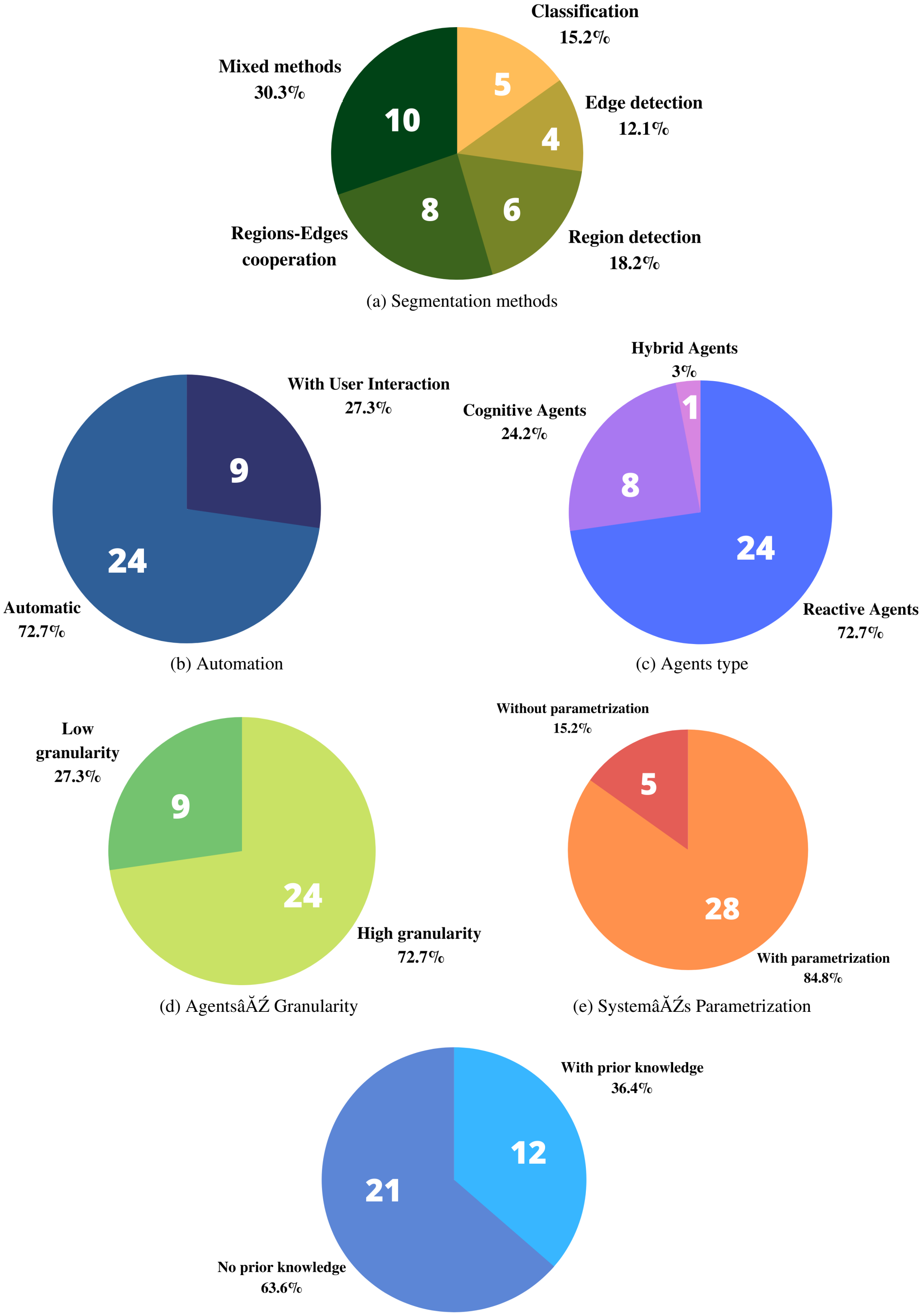
Table 2: A literature review of MAS approaches for medical image segmentation.

	Approach	Year	Segmentation Method(s)
Classification	Scherrer et al. [42, 43, 44]	2007	MRFs
	Chitsaz et al. [47, 48, 49]	2009	Thresholding and reinforcment learning
	Benchara et al. [50, 52, 53]	2015	C-mean and FCM
	Tan et al. [54]	2019	Collaborative multi-agent learning
	Liao et al. [55]	2019	Multi-agent reinforcement learning
Edge detection	Spinu et al. [56, 57]	1995	Edge detection with error minimization
	Fekir et al. [58, 59]	2011	Active contours model
	Nachour et al. [60]	2016	Vector field convolution
	Nachour et al. [62]	2018	Fuzzy logic and active contours model
Region detection	Liu et al. [26]	1999	Multi-agent diffusion, breeding, and labelling
	Richard et al. [63]	2004	Region growing
	Benamrane et al. [64]	2007	Region growing and region merge
	Fleureau et al. [66]	2009	Region growing
	Pereira et al. [73]	2014	Filtering, edge following and region growing
	Bennai et al. [67]	2017	Region growing and region merge
Regions-Edges Cooperation	Germond et al. [68]	2000	Deformable model, edge detector, and region growing
	Porquet et al. [69]	2003	Deriche edge detector and quad-tree method
	Idir et al. [72]	2005	Canny edge detector and region growing
	Nachour et al. [74, 75]	2015	Seeded region growing and thresholding
	Allioui et al. [76, 77]	2016	Multi-agent image analysis and segmentation
	Bennai et al. [78]	2020	K-means, region growing and region merge
	Bennai et al. [79]	2020	K-means, region growing and region merge
Mixed methods	Boucher et al. [81, 82]	1997	Region growing, thresholding and region merge
	Duchesnay et al. [84, 85]	2001	Quad-tree, merge region, and edge detection
	Bovenkamp et al. [88, 89, 90]	2003	Agent cooperation
	Haroun et al. [86]	2005	FCM, region growing and region merge
	Shariatpanahi et al. [87]	2006	M-Rep deformable models and FCM clustering algorithm
	Moussa et al. [91]	2009	Social-ants and social-spiders
	Moussa et al. [92, 39]	2010	Social-spiders and thresholding
	Allioui et al. [93, 94, 95]	2019	Super pixels, game theory, and region merge
	Allioui et al. [96]	2020	Combining region growing with PSO

Table 3 and Fig. 2 also bring attention to the common issues of agent-based medical image segmentation systems. Accordingly, we notice that 27.3% of the reviewed approaches still need user intervention to perform the segmentation process, whereas 72.7% are fully automatic. Thus, 36.4% of studied MASs base their segmentation on prior knowledge. This reliance limits the possibility of generalization and increases the risks of overfitting. Finally, the most common drawback of these MASs is their need for parametrization. Thus, nearly 84.8% of the MAS approaches discussed in this review require an empirical determination of several parameters. This problem limits their use under realistic conditions.

Table 3: The characteristics of the reviewed multi-agent approaches for medical image segmentation.

	Approach	Semi-auto	Agents Type	Granularity	Parameters	Prior knowledge
Classification	Scherrer et al. [42, 43, 44]	No	Reactive	High	Yes	Yes
	Chitsaz et al. [47, 48, 49]	No	Reactive	High	Yes	Yes
	Benchara et al. [50, 52, 53]	No	Reactive	High	No	Yes
	Tan et al. [54]	No	Cognitive	Low	Yes	Yes
	Liao et al. [55]	Yes	Reactive	High	Yes	Yes
Edge detection	Spinu et al. [56, 57]	No	Cognitive	High	Yes	Yes
	Fekir et al. [58, 59]	Yes	Reactive	High	Yes	No
	Nachour et al. [60]	No	Reactive	High	Yes	No
	Nachour et al. [62]	Yes	Reactive	High	Yes	No
Region detection	Liu et al. [26]	No	Reactive	High	Yes	Yes
	Richard et al. [63]	No	Reactive	High	Yes	No
	Benamrane et al. [64]	No	Reactive	High	Yes	No
	Fleureau et al. [66]	Yes	Hybrid	Low	Yes	Yes
	Pereira et al. [73]	No	Reactive	High	Yes	Yes
	Bennai et al. [67]	No	Reactive	High	Yes	No
Regions-Edges cooperation	Germond et al. [68]	No	Reactive	High	Yes	Yes
	Porquet et al. [69]	No	Reactive	High	Yes	No
	Idir et al. [72]	No	Reactive	High	Yes	No
	Nachour et al. [74]	No	Reactive	Low	Yes	Yes
	Nachour et al. [75]	No	Reactive	Low	Yes	No
	Allioui et al. [76, 77]	Yes	Cognitive	Low	No	Yes
	Bennai et al. [78]	No	Reactive	High	No	No
	Bennai et al. [79]	No	Reactive	High	Yes	No
Mixed methods	Boucher et al. [81, 82]	No	Cognitive	High	Yes	Yes
	Duchesnay et al. [84, 85]	No	Reactive	High	Yes	No
	Bovenkamp et al. [88, 89, 90]	Yes	Cognitive	Low	Yes	No
	Haroun et al. [86]	No	Reactive	High	Yes	Yes
	Shariatpanahi et al. [87]	Yes	Cognitive	Low	Yes	Yes
	Moussa et al. [91]	No	Reactive	High	Yes	No
	Moussa et al. [92, 39]	No	Reactive	High	Yes	No
	Allioui et al. [93]	Yes	Cognitive	Low	No	Yes
	Allioui et al. [94, 95]	Yes	Cognitive	Low	No	Yes
	Allioui et al. [96]	No	Reactive	High	Yes	Yes



(a) Segmentation methods

(b) Automation

(c) Agents type

(d) AgentsâĂŹ Granularity

(e) SystemâĂŹs Parametrization

(f) Prior knowledge use

Fig. 2: MASs distribution according to several characteristics

7. Conclusion

MASs represent a relatively recent technology adopted for problem-solving in many different domains. Offering many functional capabilities such as cooperation, distribution, and responsiveness, they have gradually become an interesting lead for many research areas, including healthcare. Image processing, and more precisely, image segmentation where various agent-based methods have been proposed.

After providing the essential information about MASs, this article presents a non-exhaustive survey of different agent-based image segmentation techniques published in the literature. First, multi-agent image segmentation systems have been introduced according to the type of images they process. This review illustrates the potential of MAS segmentation methods with different types of images, including satellite images, range images, and photographic images. Then, the current state of the art of MASs for medical image segmentation has been addressed explicitly in a dedicated review, focusing on the specific problems of this type of images. Thus, the dedicated section presented several MAS approaches using our proposed detailed classification. Therefore, this review highlighted the effectiveness of each approach and pointed out the detected drawbacks. Finally, a discussion resumed the common characteristics of MASs for medical image segmentation, as well as a list of the most widespread drawbacks.

From this study, we deduced several critical aspects of MAS development for medical image segmentation, including the effectiveness of various segmentation approaches when coupled with the MASs and their drawbacks. The flexibility provided by the MAS paradigm allows the mix of many different methods in one segmentation system. It also allows the apparition of new original solutions based on agents' cooperation and interaction. However, there are less multi-agent segmentation approaches than other artificial intelligence techniques such as machine learning.

By their nature, except for emergent [34] or bio-inspired [24] approaches, the significant contribution of MASs to the field of image segmentation is the distribution of the segmentation process and the coordination of heterogeneous methods to guarantee the quality of the segmentation results. An example of an effective design of a multi-agent segmentation system uses conventional detection methods and integrates them to ensure overall system functionality, allowing for improved segmentation results: For example, a MAS may use conventional detection methods and integrate them to ensure overall the quality of segmentation. Moreover, machine learning methods like deep learning are increasingly attracting researchers' attention due to their impressive results for medical segmentation. They are based on analyzing large sets of ground truth data. This need for training data is the main limitation for machine learning approaches in specific domains like healthcare.

Therefore, with their flexibility and capacity to operate with no training data sets, multi-agent medical segmentation approaches can greatly support machine learning methods when no training data are available. This support can be made effective, for example, by using MAS approaches for the initial segmentation of a large number of images. These images can then be checked and, if necessary, corrected by experts. This procedure could reduce the time and effort needed to build a dataset of images that can then be used to train deep-learning models. Furthermore, the last years brought significant advancements in both multi-core computing capabilities (improving multi-agent segmentation performances) and machine learning dedicated hardware. This progress offers the researchers an opportunity to design real-time medical image segmentation systems by combining machine learning and MASs.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Highlights

- A systematic review synthetizing published agent-based medical image segmentation works.
- An introduction to the several domains of application of the agent-based image segmentation methods
- The presentation of state-of-the-art multi-agent systems for medical image segmentation according to our proposed classification
- A discussion highlighting the common characteristics of multi-agent systems for medical image segmentation, as well as their drawbacks
- A conclusion that summarizes the key features of multi-agent systems for medical image segmentation and suggest promising directions for future work