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RESEARCH ARTICLE

Image Segmentation by Agent-Based Pixel Homogenization

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ABSTRACT Image segmentation is the process of partitioning an image into multiple regions or objects, each representing a coherent and meaningful part of the image. Segmentation methods are highly sensitive to the lack of homogeneity in regions or objects owing to noise and intensity inconsistencies. Under such conditions, most approaches exhibit poor quality performance. This paper proposes an agent-based model approach for homogenization of images to reduce the presence of noisy pixels and undesirable artifacts. In our approach, each pixel in the image represents an agent, and a set of rules evaluates the states of neighboring agents to modify the intensity values of each pixel iteratively until different regions from the image assume homogeneous grayscale levels. The proposed method has been used in combination with the Otsu's method to evaluate its performance in image segmentation. The approach was evaluated with different types of images considering their homogeneity. Experimental results indicated that the proposed approach produces better-segmented images in terms of quality and robustness.

INDEX TERMS Agent-based model, binarization, pixel homogenization, segmentation.

I. INTRODUCTION

Image segmentation is an area of image processing that has attracted the interest of several researchers because its multiple applications [1], [2]. Image segmentation is a process of dividing an image into different regions. The objective of this process is to reduce the representation complexity of an image into a few and more meaningful elements that require simpler analysis [3], [4]. There are multiple applications of image segmentation. Some examples include medical imaging, face recognition, to name a few. Various segmentation methods have been reported in the literature. Some of the most popular segmentation techniques include region-based segmentation methods [5], threshold-based segmentation methods [3], [4], clustering-based segmentation methods [6], edge detection-based segmentation methods [7], and active-contour-based segmentation methods [8], [9]. Each of these presents interesting characteristics and critical flaws. Under these conditions, no segmentation approach can solve all segmentation scenarios competitively.

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Thresholding methods are considered to be the simplest approach for image segmentation. Their operation is based on detecting the peaks in the image histogram, which represent the regions contained in the image. However, it has several disadvantages because it is highly dependent on the peaks in the histogram, and the spatial position of the pixels is not considered in the process [7]. Edge-based approaches are suitable for images with a better contrast between objects. However, it is not suitable for images with too many borders [10]. Clustering techniques are expensive in terms of computational time and require the definition of the number of objects that are difficult to determine a priori [11], [12], [13], [14]. Active contour segmentation involves the detection of object boundaries within an image by minimizing a predefined energy function that adapts a deformable curve. Active contour segmentation is typically designed for the segmentation of a single object [15]. Therefore, it is unsuitable for segmenting images with multiple objects. In general, all these techniques are affected by several factors, such as:1) the presence of noise and artifacts caused by the techniques used for the acquisition, and 2) the lack of homogeneity in pixels that belong to the same region or structure [3].

Among all segmentation approaches, the Otsu's method [16] is the simplest and most computationally efficient. Otsu's method can quickly compute the optimal threshold values by analyzing the statistical properties of the image, whereas most segmentation methods require more computational resources and are time-consuming. The basic idea behind this method is to divide the image into two classes (foreground and background) by determining the optimal threshold value that separates the image intensities into two classes. This threshold value is determined by maximizing the between-class variance, which is a measure of the difference between the intensities of the two classes. Otsu's method can also be applied to multi-threshold segmentation, which involves dividing an image into multiple classes based on multiple threshold values. Owing to its remarkable capabilities, Otsu's method has been widely used in various image processing applications [17], [18], [19], [20], [21], such as object recognition, edge detection, and feature extraction.

Segmentation methods are highly sensitive to the lack of homogeneity in regions or objects owing to noise and intensity inconsistencies. This can hinder the ability of image segmentation algorithms to correctly identify and separate objects or regions. In particular, noise causes random variations in the pixel intensity values. This effect produces false or missed detections of pixels in the image of a particular object. Moreover, intensity inconsistencies occur owing to changes in illumination or other factors, which can cause variations in the intensity values of different regions of the image. This condition generates inaccuracies in the segmentation results because the method may misinterpret these intensity variations as object boundaries or regions. Under such circumstances, the segmentation algorithm incorrectly divides the image into too many segments, resulting in very small regions that do not correspond to meaningful objects in the image.

Homogenization [22] is an important process in image segmentation, as it helps to reduce the variability of pixel intensities in the image and makes it easier to detect meaningful structures. This helps to reduce the impact of intensity variations, such as noise, shadows, reflections, and changes in illumination, which can make it difficult to accurately segment the image into its constituent parts. By removing such intensity variations, homogenization can make it easier to detect boundaries between different objects in the image, and to distinguish between foreground and background regions. There are several methods for performing pixel homogenization. They include Histogram equalization [23]. This method adjusts the intensity values of pixels so that the histogram of the image has a flat distribution. Another technique is Intensity normalization. It scales the intensity values of pixels so that they fall within a specific range. This can help to reduce the impact of intensity variations caused by factors such as lighting conditions. Another important method is the Adaptive histogram equalization [24], which is similar to histogram equalization, but instead of equalizing the histogram of the entire image, it equalizes the histogram of smaller regions within the image. This can help to preserve a small proportion of local features in the image, which are lost during traditional histogram equalization. All these homogenization methods use global characteristics to conduct their processes. Global features are computed based on the entire image and therefore cannot account for local variations or spatial relationships between neighboring pixels. Therefore, these schemes can produce over-smoothing or under-smoothing of image regions and may result in the loss of important details or structures. Global features can also be strongly influenced by outliers or extreme values in an image, which can result in inaccurate homogenization results. This can be particularly problematic for images with high levels of noise or artifacts.

Recently, the use of local characteristics has emerged as an alternative for solving the problem of homogenization. In general, the use of local features produces more accurate and precise homogenization results with less oversmoothing or undersmoothing of image regions. Despite their interesting capacities, there are very few methods based on local characteristics. One exception is the recent work presented in [25], where a combination of the median filter and a set of morphological operations were applied to homogenize regions. This method can reduce variations in pixel intensities when the noise structure is very small. In addition, it can help fill small gaps or holes in the image, which can be useful for creating a more complete representation of objects or regions of interest. Although this scheme generates acceptable results, it is not always able to effectively handle the complex noise structures present in the image. Likewise, unwanted artifacts or blur may be introduced into the image when the noise structure presented in the image is larger than the employed morphological filter.

Agent-based models (ABMs) [26], [27] (ABM) represent a new paradigm within the area of artificial intelligence (AI) to model complex systems using individual elements that perform behaviors described by simple rules. In contrast to other modelling techniques that consider only global information, ABMs are completely based on the local interactions among elements. In ABMs, local relationships between individuals are typically captured through the specification of rules or behaviors that govern how agents interact with their immediate neighbors. These rules can be based on a variety of factors, such as proximity or similarity. In these models, agents are strongly influenced by collective interactions with other elements in the system. The use of local information in ABMs allows the emergence of complex collective behaviors that arise from interactions between individual agents. By considering the local relationships between agents, ABMs can simulate how simple the interactions between agents can give rise to complex patterns of behavior at the system level. These powerful characteristics have motivated the use of ABM in several applications, such as characterization of the immune system [28], social behavior [29], [30], image processing [31], image colorization [32], fire spreading [33], and spread in epidemics [34], among others [35], [36], [37].

In this article, the ABM methodology is applied as homogenization method for image segmentation. In this approach, the attributes and behaviors of the agents are associated with the pixels of the image and their respective relative differences. Each agent makes decisions based on a set of rules that determine its behavior based on its differences from other neighbor elements. In this model, each agent maintains its intensity value and the signs of the relative differences with other local elements within a neighborhood. Then, as a rule of behavior, the intensity value of the agent is incremented or decremented depending on which sign is most common among neighbors. Therefore, the intensity values of all agents are modified in each iteration to homogenize their local neighborhoods to the same intensity value. In contrast to other homogenization approaches that rely on global characteristics, our agent-based method considers local features that can capture more detailed information about image regions, including local variations and spatial relationships between neighboring pixels. Local features are also less sensitive to outliers or extreme values in the image because they only consider a small neighborhood of pixels. Under such circumstances, our proposed method produces more accurate and precise homogenization results, with less oversmoothing or undersmoothing of image regions. The Otsu's algorithm has been combined with the proposed method to assess its effectiveness in image segmentation. The approach has been evaluated with different sets of images considering their homogeneity properties. Experimental results indicate that the proposed approach is able to produce better-segmented images in terms of quality and robustness.

The remainder of this paper is organized as follows. Section II presents the agent-based model. Section III presents the main concepts of binarization and segmentation using Otsu's method. Section IV presents the design of the proposed method. The results are presented in Section V. Finally, the conclusions are presented in Section VI.

II. AGENT BASED MODEL (ABM)

An ABM [38] is a computational model that simulates the actions and interactions of set of N autonomous agents. When an agent makes decisions based on its programmed rules, it uses information regarding other neighboring agents. The selection of neighbor agents and the type of information used to modify the characteristics of an agent represent the manner in which the interactions among the agents are modeled. The rules that characterize these processes are generally very simple, such as a yes or no operation. Even though AMB approaches consider simple rules in their operation, they can generate very complex behaviors that cannot be produced and analyzed using traditional mathematical models [39].

Each agent A_i $(i \in 1, \ldots, N)$ is characterized by a vector θ_i of n attributes that can be adjusted. Therefore, the set of attributes θ_i can be formally defined as:

$$\theta_i = \left\{a_1^i, \ldots, a_n^i\right\} \tag{1}$$

The agent then assigns a value to each attribute. The agents are considered dynamic elements that change their attributes in each iteration k.

The rules define the manner in which an adjustable attribute a_j^i of agent A_i is modified [26], [27]. In general, rules are represented as IF-THEN structures. Therefore, the rules consist of two parts: the antecedent and consequent. The antecedent (IF part) refers to the conditions under which an attribute or set of attributes is modified. Typically, an antecedent involves a function $f(A_i)$ that associates the attributes of agent θ_i with the attributes of other agents within its neighborhood N_i. This function is formulated as follows:

$$f\,(A_i) = f(\theta_i, |\theta_1, \ldots, \theta_m|) \tag{2}$$

where $\theta_1, \ldots, \theta_m$ represent the attributes of the agents $\{A_1, \ldots, A_m\}$ within the neighborhood N_i of A_i.

On the other hand, the consequent represents the magnitude in which an attribute a_j^i of the agent A_i is modified. The main component of the antecedent consists of a function $g(a_j^i)$ that modifies the value of a_j^i in iteration k to produce a new value for iteration $k+1$. Therefore, the adjustment of attribute a_j^i can be modelled as follows:

$$a_j^i\,(k+1) = a_j^i\,(k) + g(a_j^i) \tag{3}$$

III. IMAGE SEGMENTATION EMPLOYING OTSU CRITERION

The Otsu method [16] is one of the most popular segmentation techniques for thresholding, with a wide range of applications. Otsu's method allows determination of the optimal threshold value to segment an image using information obtained from the histogram of an image [40]. The histogram H of an image in its corresponding intensity value is defined by the following formulation:

$$H = \{h_0 + h_1 + \ldots + h_{L-1} \tag{4}$$

where h_r is the occurrence frequency of the gray level r in the image. $\sum_{r=0}^{L-1} h_r$ represents the total number of pixels. L represents the number of intensity values that an image can represent. The probability of occurrence p_r of each r intensity value is determined as follows [17]:

$$p_r = h_r/N \tag{5}$$

In case of two classes A and B, the algorithm conducts a searching process to find the threshold that minimizes the intra-class variance σ_ω^2, which is defined as a sum of weighted variances of the two classes.

$$\sigma_\omega^2\,(T) = \omega_A\,(T)\,\sigma_A^2\,(T) + \omega_B\,(T)\,\sigma_B^2\,(T) \tag{6}$$

The threshold value T that gives the minimum intra-class variance is chosen as the optimal threshold. The probabilities of the two classes A and B, which are divided by a threshold

T, are represented by weights ω_A and ω_B. Variances σ_A^2 and σ_B^2 correspond to the two classes. The probabilities of classes ω_A and ω_B are calculated by taking into account the L gray scale values in the following way:

$$\omega_A(T) = \sum_{i=0}^{T-1} p_i \quad \omega_B(T) = \sum_{i=T}^{L-1} p_i \tag{7}$$

The Otsu method can be used for two-class thresholding, where the goal is to segment an image into two regions (considering only one threshold T), or multi-thresholding, where the goal is to segment an image into R regions (considering several thresholds $T_1, \ldots, T_{R-1}$). In multi-thresholding, the Otsu's method calculates multiple threshold values to segment the image into multiple regions. This is done by iteratively applying the two-class Otsu method to a histogram of the image, with the goal of identifying multiple peaks in the histogram that correspond to different regions in the image. Each peak is then used to define a threshold value, and the image is segmented into multiple regions based on these threshold values.

IV. IMAGE SEGMENTATION BY ABM

In this section, we describe our proposed approach which is a segmentation method that combines the Otsu method with an agent-based model. The aim of our approach is to use the Otsu method to find the threshold points for image segmentation, while the agent-based model performs the homogenization process. The Otsu method is a widely used thresholding technique that calculates the optimal threshold for image segmentation based on the histogram of the image. This method works well for images with bimodal histograms but can produce inaccurate results for images with complex histograms or when different thresholds are considered. To overcome this limitation, we propose an agent-based model that performs the homogenization process. The model consists of a group of agents that perform a set of operations to make the image more homogeneous. The agents are guided by a set of rules that are designed to promote the homogeneity in the image. The combination of the Otsu method and the agent-based model allows us to find the optimal threshold points while at the same time homogenizing the image. This approach is particularly useful for image segmentation tasks that require accurate identification of objects or regions of interest.

Our approach is divided into two distinct phases that work together to produce optimal results. In the first phase, the Otsu method is applied to identify the initial multi-threshold values required for segmenting the image into multiple regions. In the second phase, the agent-based model is applied to select the correspondence of each pixel to its corresponding threshold. In this phase, each pixel is classified as belonging to a specific region based on the threshold values identified in the first phase. Moreover, in the second phase, the regions are homogenized, which means that the pixels within each region are made more uniform in terms of their intensity values. This homogenization process improves the overall quality of the image by making each region more visually consistent. Fig. 1 present an illustration of this process.

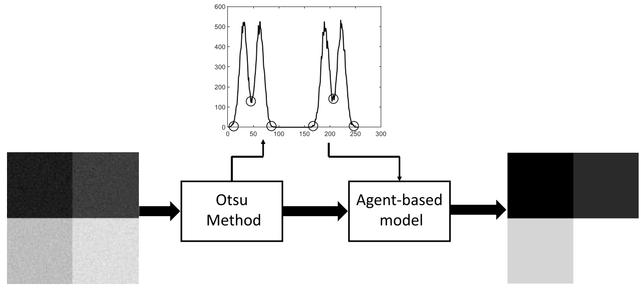


FIGURE 1. The proposed approach divided into two phases: The Otsu method and the agent-based model.

A. FIRST STAGE. APPLY THE OTSU METHOD

During the initial stage, the Otsu technique is utilized to detect the set of V threshold values $(T_1, \ldots, T_V)$ that are necessary to divide the image into V different segments. Here are the steps to obtain the threshold values through the Otsu method from a grayscale image:

1. Calculate the histogram H
2. Compute the probability of occurrence p_r of each intensity value.
3. Determine the probabilities of classes ω_A and ω_B
4. Obtain the variances σ_A^2 and σ_B^2 correspond to the two classes
5. Identify the threshold T_1 that minimizes the intra-class variance σ_ω^2
6. The steps 3-5 are iteratively applied with the goal of identifying multiple thresholds $T_2, \ldots, T_V$ corresponding to peaks in the histogram H.

B. SECOND STAGE. AGENT-BASED MODEL FOR HOMOGENIZATION

In the second phase, an agent-based model classifies the pixels into distinct types based on previously established threshold. Additionally, homogenization of the regions occurs, resulting in a more uniform distribution of intensity values among the pixels within each region.

A complex system is composed of multiple agents or elements that follow a set of rules for interaction, cooperation, or competition with each other. These rules determine how the agents respond to interactions with other agents. An image can be thought as a complex system where numerous basic agents, or pixels, present various states and interact with their close members. Through these interactions, diverse associations can be established using rules, which are used to address several image processing tasks.

Our agent-based model considers each pixel $p_{i,j}$ as an agent $A_{i,j}$ and its neighborhood of $n \times n$ as its area of influence. In this model, each pixel $p_{i,j}$ is treated as an individual agent $A_{i,j}$ that interacts with its neighboring pixels to promote homogeneity in the region. The behavior of each agent in this model is determined by the intensity differences with its neighboring pixels. Specifically, the intensity differences are evaluated based on the sign of the differences. The goal of the agents in this model is to homogenize regions by setting rules that determine whether each agent should increase or decrease its value in order to promote homogeneity in its neighborhood. The rules are designed based on the majority of the signs of the differences between the agent and its neighbors.

The agent-based model is a simulation technique used to model complex systems by defining a set of rules governing the behavior of individual agents within the system. The agent-based model is an iterative process, which means that it proceeds through a series of steps or iterations. In the beginning, each agent $A_{i,j}$ assumes an initial value that corresponds to the actual intensity value of its corresponding pixel $p_{i,j}$ in the image. These initial values serve as the starting point for the simulation. Once the initial values have been set, each agent in the model behaves according to the defined rules. As the simulation progresses through each iteration, the values of each agent $A_{i,j}(k)$ can be modified in the next iteration $k+1$ as a consequence of the rules. This means that the intensity values of the agents can change over time, as the agents interact with each other and respond to changes in their environment. The rules are applied to all pixels in the image, resulting in a new image that stores the temporary segmentation outcomes. This new image has same size as the original, but with pixels classified into different levels based on the thresholds determined by the Otsu approach. All this process is executed until a maximal number of iterations *maxIter* has been reached. Fig. 2 presents an illustration of the process conducted by the agent-based model.

In this part, we will discuss the rules used in our approach to homogenize the pixels in the neighborhood and to classify the pixels into different levels based on the threshold to which they belong.

To homogenize the pixels in the neighborhood, we first define a window size of 3×3, which determines the size of the area around each pixel (agent) that we will consider. This neighborhood is shown in Fig.3.

Every agent A_0 evaluates its intensity level against its adjacent agents A_i ($i \in 1, \ldots, 8$), resulting in eight distinct comparisons. These comparisons produce eight differences s_i, which are defined according to their sign in the following manner:

$$s_i = sign(A_0 - A_i) \tag{8}$$

In order to evaluate the homogeneity of the block, the total sign S is defined. The total sign of a neighborhood represents the sign of the majority of the elements in the neighborhood. It is formulated as follows:

$$S = sign\left(\sum_{j=1}^{8} s_i\right) \tag{9}$$

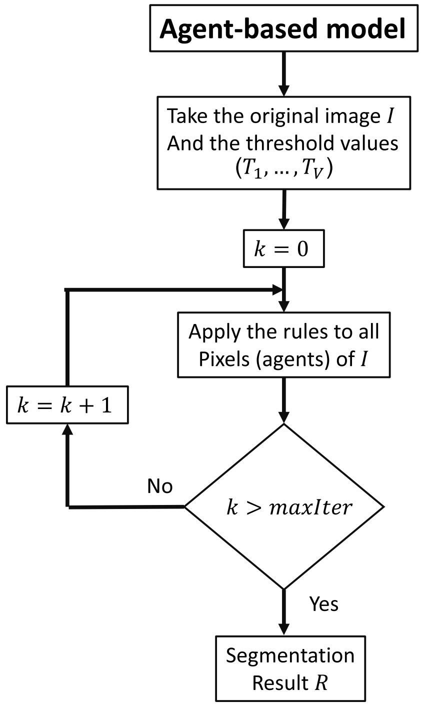


FIGURE 2. Process conducted by the agent-based model.

A_1	A_2	A_3
A_4	A_0	A_5
A_6	A_7	A_8

FIGURE 3. Neighborhood considered in the rules.

The total sign S of a neighborhood can take on three possible cases, each with different implications for the behavior of the elements in the neighborhood. These cases are positive, negative, and zero.

Our model consists of four rules. The first three rules consider the homogenization process while the fourth one allows to classify the pixels.

C. RULE I

If S has a negative value, it indicates that most of the values in the neighborhood are greater than the value of A_0. Therefore, in rule 1, if an agent A_0 has more neighbors with higher values, the majority rule suggests that the agent should increase its value in order to homogenize the contain of the block. This rule can be expressed as follows:

$$\textbf{IF}(S = -1)\textbf{THEN}\,\{A_0\,(k+1) = A_0\,(k) + \beta\} \tag{10}$$

where β represents the factor whit which A_0 is incremented. It is important to remark that the value of A_0 is protected. Therefore, it cannot assume a value greater than 255 or lower than zero.

D. RULE II

If the total sign S is positive, this means that the majority of the elements in the neighborhood have a value that is lower than A_0. So, in accordance with rule 2, if an agent A_0 has a larger number of neighbors with smaller values, the agent must decrease its own value to make uniform the content of the block. This rule can be formulated as follows:

$$\mathbf{IF}(S = 1)\mathbf{THEN}\{A_0(k+1) = A_0(k) - \beta\} \tag{11}$$

E. RULE III

The third rule considers the case when the total sign S is zero. This case has two situations. The first one is that the neighborhood is homogeneous, meaning that all the elements have the same value as A_0. The second interpretation is that the neighborhood is divided into two halves with different values, which could indicate that A_0 represents an important characteristic of the image, such as an edge or corner. In image processing, this could indicate a region of transition between two different features in an image. Therefore, If the total sign S is zero, the agent must remain without changes in order to maintain the homogeneity of the block or the presence of the feature. This rule can be expressed as follows:

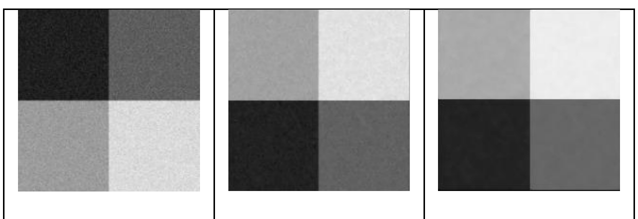
$$\mathbf{IF}(S = 0)\mathbf{THEN}\{A_0(k+1) = A_0(k)\} \tag{12}$$

F. RULE IV

Rule 4 involves the classification of pixels into different levels based on the thresholds determined by using the Otsu approach. Under this rule, the temporary segmentation results are collected in the resulting image R. The rule assigns each pixel (agent) in the image to a specific level based on the threshold it corresponds to. Specifically, if the intensity value $p_{i,j}$ of an agent $A_{i,j}$ falls within the interval $\left[T_q \leq p_{i,j} < T_{q+1}\right]$ defined by the threshold q, then the pixel in the same position as $A_{i,j}$ is set to q in the new image R that collects the temporary segmentation results. This rule can be formulated as follows:

$$IF(T_q \leq A_{i,j} < T_{q+1})THEN\left\{R_{i,j} = q\right\} \tag{13}$$

The effects of the application of this rule along with the other rules can be seen in Figure 4. The figure shows the results of the agent-based model in iterations 1, 10 and 20.



(a) 1 (b) 10 (c) 20

FIGURE 4. Results of the agent-based model in iterations (a) 1, (b) 10 and (c) 20.

V. EXPERIMENTAL RESULTS

In this section, the performance of our proposed approach, called ABM-Seg, is analyzed. The proposed approach is tested by considering different public datasets commonly used in the literature. The results have been compared with those obtained using other homogenization schemes. The objective is to provide evidence of the effectiveness of the proposed method in segmenting and simultaneously increasing the homogeneity index of the images.

This section is divided into three subsections. First, we introduce the homogeneity index used to evaluate the segmentation results. In the second subsection, the ABM-Seg and Otsu methods are compared in terms of their homogeneity using a representative set of images. Finally, in the third subsection, the proposed method is compared with another state-of-the-art homogenization approach.

A. HOMOGENEITY INDEX

Segmentation refers to the partitioning of an image into different regions that correspond to distinct objects or parts of interest. To evaluate the effectiveness of segmentation algorithms, various metrics have been proposed [41]. However, the use of segmentation indexes alone is not sufficient to evaluate an appropriate segmentation. Even if a segmentation algorithm achieves a high score on a certain index, it may not result in a segmentation that is visually or semantically meaningful. Therefore, it is also important to evaluate the homogeneity of the segmentation results, which refers to the degree of similarity or consistency within each region. Homogeneity is a crucial aspect of segmentation quality, as it ensures that each region corresponds to a meaningful object or part of the image, and that there are no disjoint or overlapping regions that cause confusion or misinterpretation. Unfortunately, there are no indexes that are able to appropriately assess the homogeneity of regions.

In this study, a homogeneity index is proposed based on the gray level co-occurrence matrix (GLCM) [42]. It computes the frequency of occurrence of different combinations of gray-level values and generates a matrix that summarizes the texture or homogeneity of the image. By analyzing the GLCM for each region in a segmentation, it is possible to derive a homogeneity index that quantifies the degree of similarity between the gray-level distributions within the region.

To produce a gray level co-occurrence matrix (GLCM) from image I, it is calculated how often a pixel with gray level value i appears horizontally next to a pixel with value j. Each element (i, j) in GCLM specifies the number of times that the pixel with value i is horizontally adjacent to a pixel with value j. Figure 5 shows how various values are calculated in the GLCM of the 4-by-5 image I. The element (1,1) in the GLCM contains the value 1 because there is only one instance in the image where two horizontally adjacent pixels have the same values. values 1 and 1. The element (1,2) in the GLCM contains the value 2 because there are two instances in the image where two horizontally adjacent pixels have the values 1 and 2. This process continues until completing all the values in the GLCM [43].

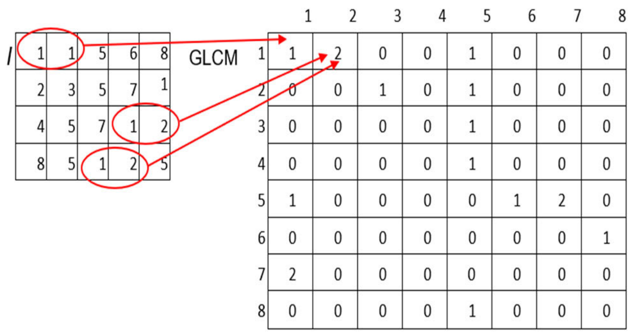


FIGURE 5. **Creating a gray level co-occurrence matrix.**

Once the GLCM is obtained such that the sum of its elements is equal to 1. Each element (i, j) in the normalized GLCM corresponds to the probability of the joint appearance of pixel pairs that presents a defined spatial relationship in terms of the gray level values i and j in the image. Subsequently, the homogeneity, H, was calculated using Equation 8. $P_{i,j}$ is the probability of the co-occurrence of gray values i and j for a given distance. A higher value represents a more homogeneous image [44].

$$H = \sum_{i,j=0}^{N-1} P_{i,j}/1 + (i-j)^2 \tag{14}$$

The proposed homogeneity index H based on GLCM has several advantages. First, it is able to capture both the texture and contrast characteristics of regions, which are important for determining their homogeneity. Second, it is easy to compute and does not require any ground truth data or reference segmentation. Third, it is applicable to a wide range of image types and segmentation algorithms and can be used to compare different segmentations based on their homogeneity scores.

B. ABM-SEG COMPARED WITH THE OTSU METHOD

In our experiment, the Otsu method has been implemented in its standard form whereas the proposed technique uses a beta factor β with a value of 1 and is run for 200 iterations. The number of iterations is chosen to ensure that the technique is fully converged, and the resulting segmentations are also stable. To evaluate the performance of the new technique, a range of threshold values, $T_i = \{2, 3, 4, 5\}$, were applied to all images. This was done to explore the sensitivity of the new technique to different threshold values and to provide a comprehensive evaluation of its performance. All experiments were performed using MATLAB 9.1.3 on a computer with a 1.8 GHz AMD Ryzen 7 CPU and 16 GB of RAM. This setup was chosen to ensure that the experiments were conducted efficiently and without significant computational overhead.

This subsection includes a set of experiments that aim to evaluate the effectiveness of the ABM-Seg algorithm in producing homogeneous segmentations compared to the Otsu method. The experimental tests were conducted using a representative set of images. The homogeneity of the segmentations is considered the main evaluation criterion. The comparison considers two important aspects: Visual and numerical.

The visual comparison involves the visual evaluation of a set of images to determine the quality of the segmentation results. This is an important aspect of evaluation as it allows a qualitative assessment of how well an algorithm is able to accurately segment objects in an image. By visually comparing different images, it becomes possible to identify any inaccuracies or artifacts that might be present in the segmentation results. This helps in determining the visual quality of the segmentation produced by the algorithm.

The second aspect of comparison considers the numerical comparison of the homogeneity index among different images. By comparing the homogeneity index among different images, it becomes possible to quantitatively evaluate the performance of different segmentation algorithms. A higher homogeneity index indicates a more homogeneous segmentation, and thus a better segmentation result.

By considering both visual and numerical comparisons, it becomes possible to make a comprehensive assessment of the performance of different segmentation algorithms. While the visual comparison allows for a qualitative evaluation of the segmentation quality, the numerical comparison provides a quantitative measure of the homogeneity of the segmentation results. This allows for a more objective evaluation of different segmentation algorithms and helps to identify the strengths and weaknesses of each algorithm.

1) VISUAL EVALUATION

For the visual evaluation, a set of images consisted of six representative images are considered. They are shown in Figures 6-11. Each figure includes the original image, follows by four segmented images produced by the ABM-Seg algorithm for the number of thresholds {2,3,4,5}. These segmented images were labeled as (a-d) in the table. To better assess the homogeneity of the segmentations, significant zoomed versions of the segmented images were presented in images (e-h). Each figure contains also set of images consisted of segmented results of the Otsu method, and their corresponding segmentations were presented in elements (i-l). Like the ABM-Seg results, the center of each segmented image was zoomed to better appreciate the homogeneity of the segmentation. These zoomed images were presented in elements (m-p).

Based on a visual inspection of figures 6-11, it is evident that the proposed ABM-Seg approach outperforms the Otsu method in terms of segmentation quality. Three main aspects have been identified to support this claim. Firstly, the ABM-Seg approach produces segmentation results that are more homogeneous, with an excellent degree of similarity or consistency within each region. This results in visually or semantically meaningful areas, which are easily interpretable. In contrast, the Otsu method produces

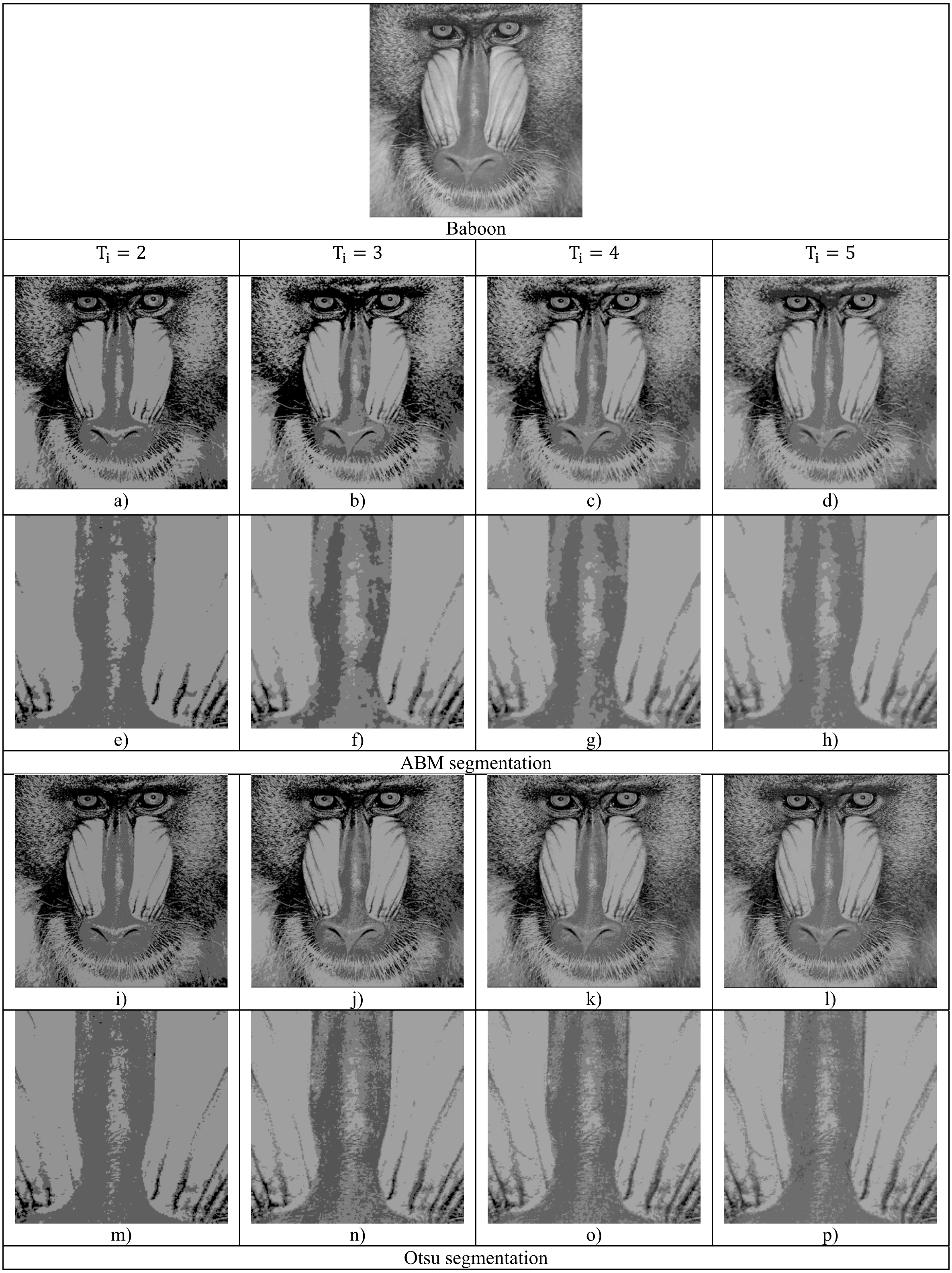


FIGURE 6. **Segmentation results evaluated over the Baboon image.**

inhomogeneous results that are visibly fragmented and disjointed. The ABM-Seg approach is therefore able to produce a more accurate and reliable segmentation of the image.

Secondly, the ABM-Seg approach produces segmented results with a low presence of artifacts or noise elements. This is evident in all the images, where the ABM-Seg

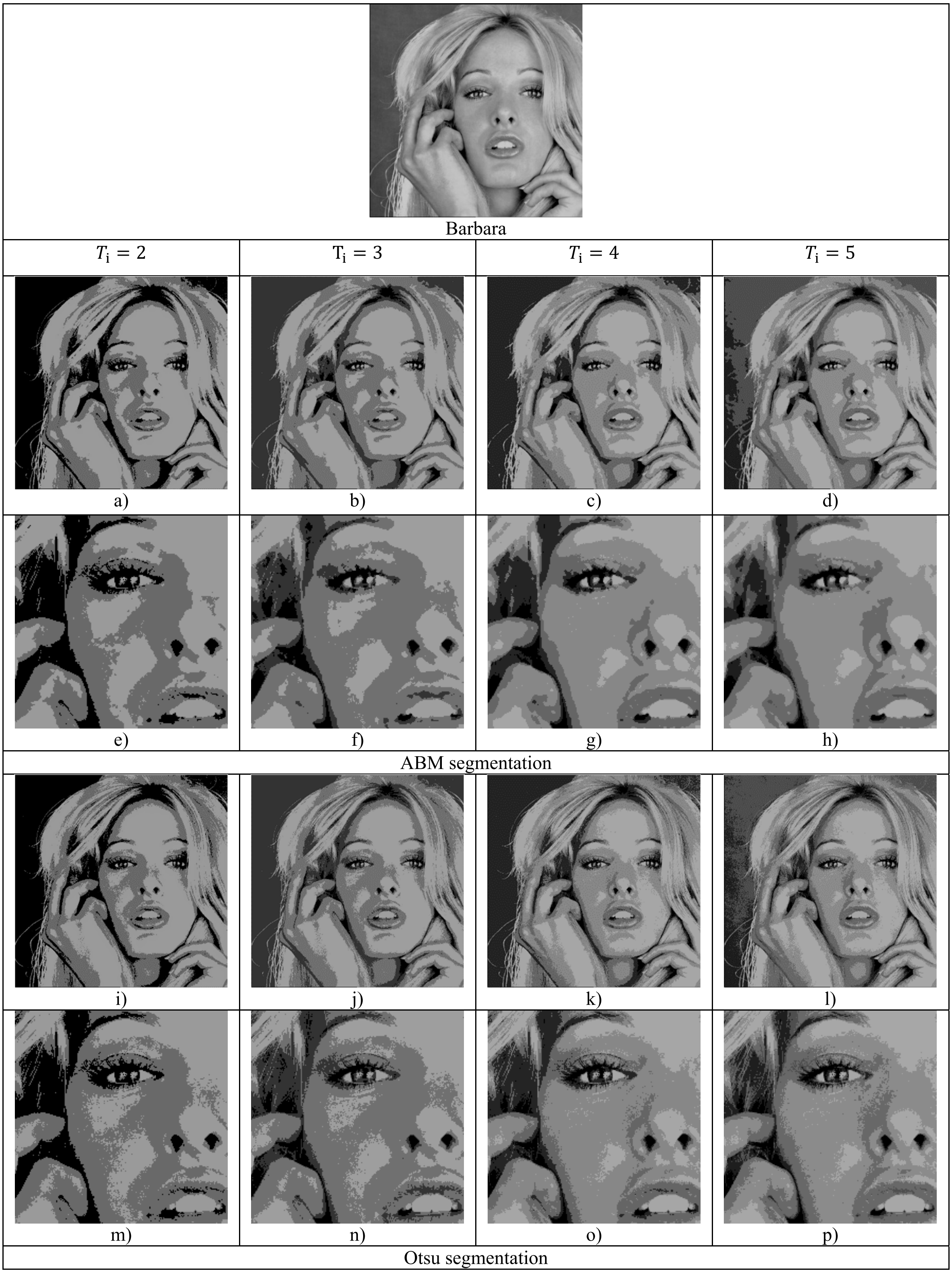


FIGURE 7. **Segmentation results evaluated over the Barbara image.**

approach produces clean and smooth edges, with no apparent noise or distortion. On the other hand, the Otsu method is more prone to producing noisy elements that result in discontinuous regions. This can lead to inaccurate segmentation results and can impact the overall quality of the image. Thirdly, the ABM-Seg approach preserves the important

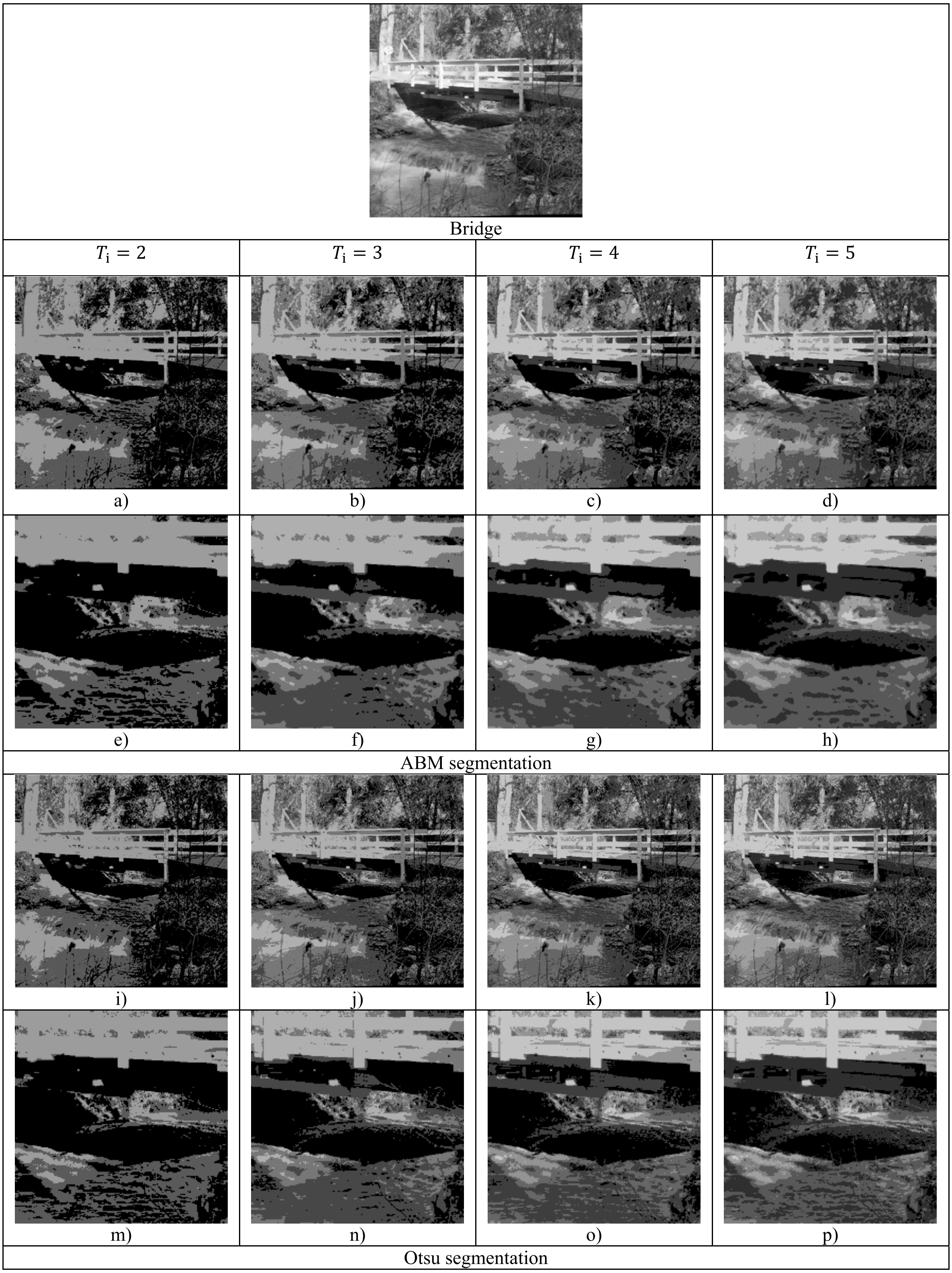


FIGURE 8. Segmentation results evaluated over the Bridge image.

features of the image, such as corners and edges. These features are not affected by the operation of the agent-based model and are preserved in the segmented result. In contrast, the Otsu method is known to remove or alter these important features in some cases, resulting in inaccurate segmentation results. The ability of the ABM-Seg

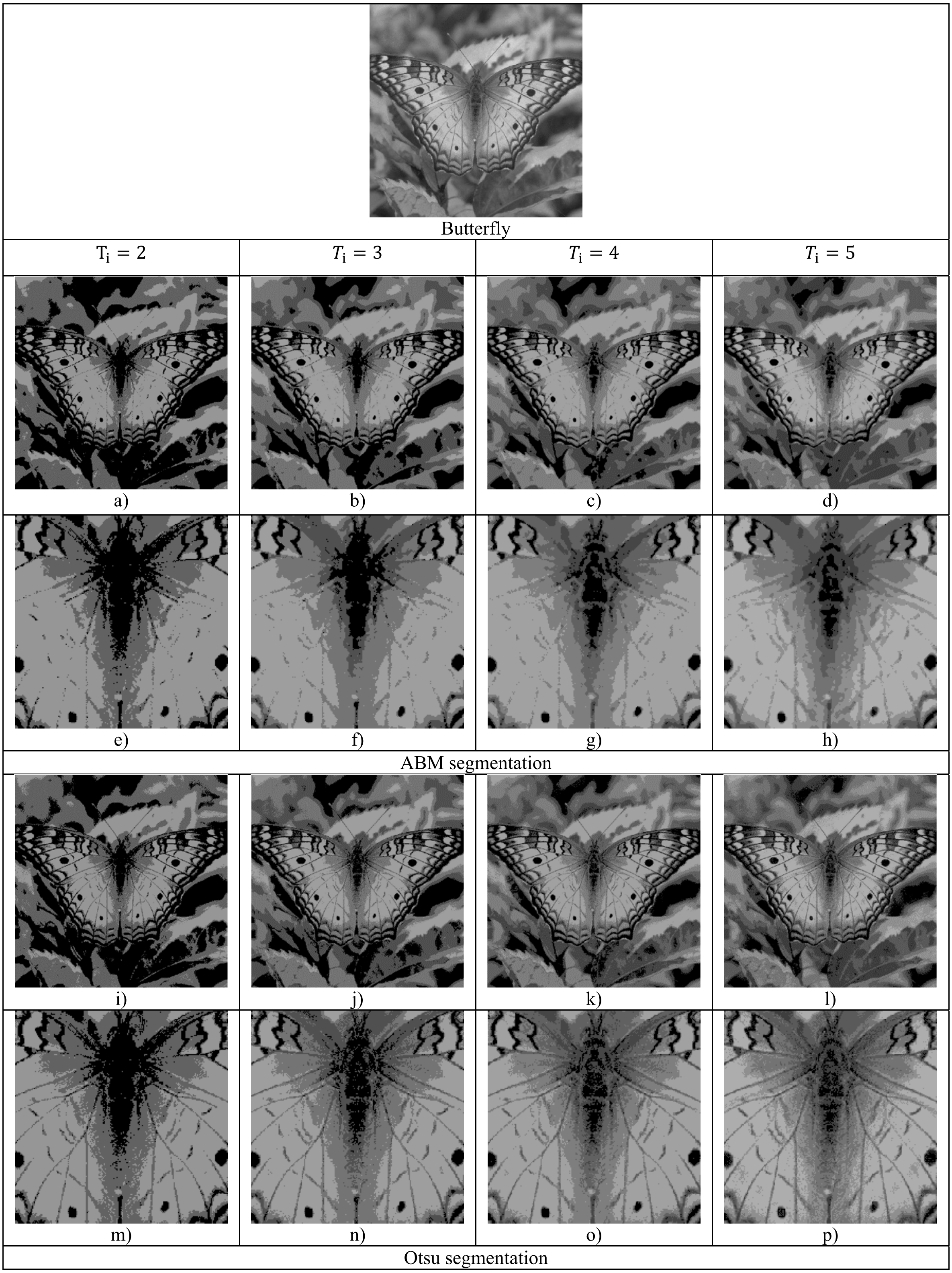


FIGURE 9. Segmentation results evaluated over the Butterfly image.

approach to preserve these features is a significant advantage and makes it a more reliable approach for image segmentation.

On the other hand, in the Figures 6-11 that have been increased in size such as (e-h) or (m-p), finer details become more apparent. As we analyze these images, it becomes clear

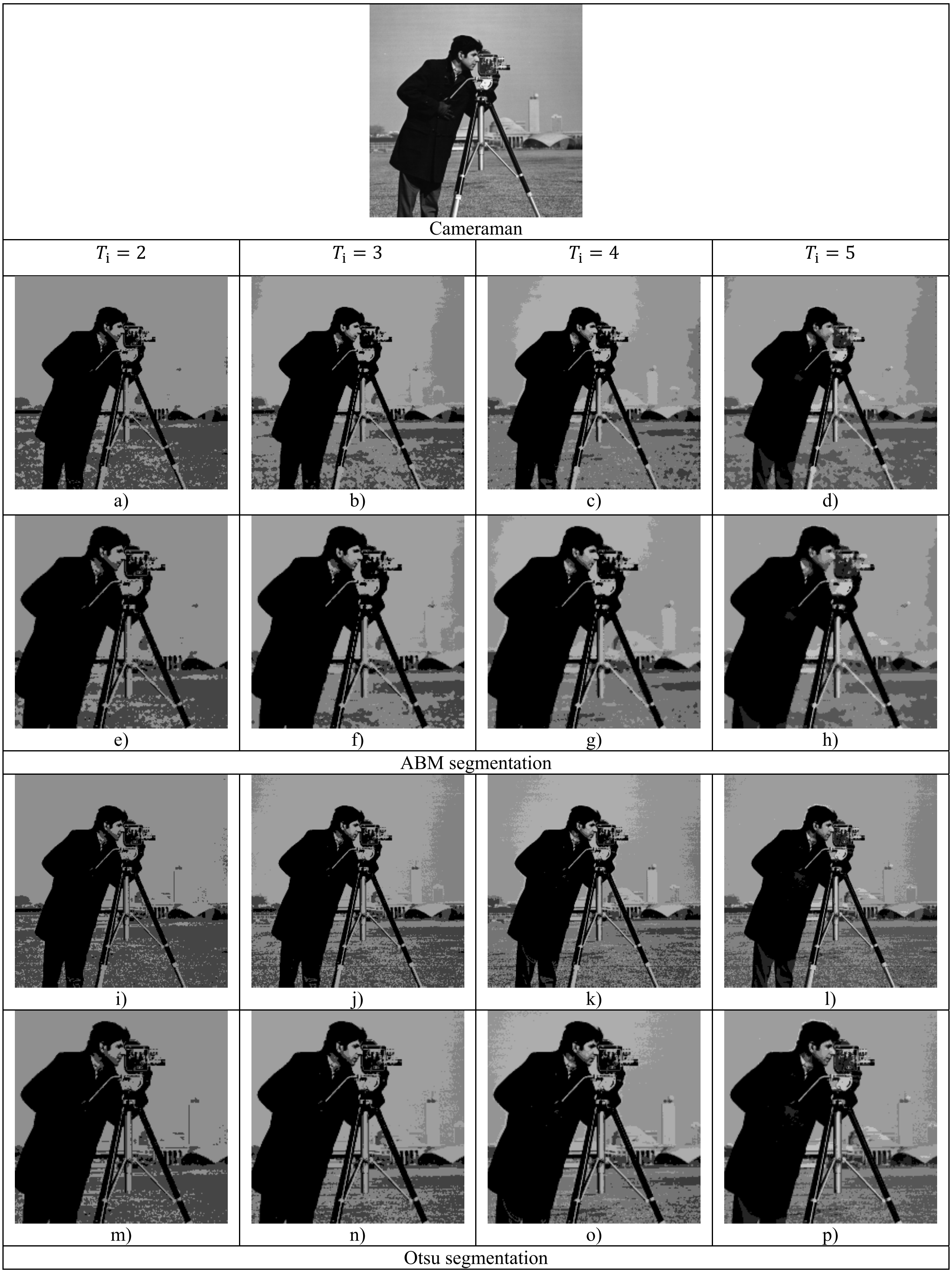


FIGURE 10. **Segmentation results evaluated over the Cameraman image.**

that the ABM-Seg algorithm produces boundaries which match the true edges of the objects. In contrast, the Otsu method generates boundaries that are not accurate with the visual edges from the images. This suggests that the ABM-Seg algorithm is more effective at accurately segmenting objects in images. Moreover, it is evident from the images

FIGURE 11. Segmentation results evaluated over the Lena image.

that the ABM-Seg method presents a lower number of inaccuracies or artifacts in comparison to the Otsu approach. This further highlights the superior accuracy of the ABM-Seg algorithm. In general, from the images, it is visually evident that the ABM-Seg algorithm allows the accurate detection of each important region or object in the image, while the

TABLE 1. Homogeneity (H) values for images from Figures 6-11.

Image	Baboon		Barbara		Bridge	
	Or: 0.7827		Or: 0.8901		Or: 0.8251	
T_i	ABM-Seg	Otsu	ABM-Seg	Otsu	ABM-Seg	Otsu
2	**0.8755**	0.8443	**0.9469**	0.9259	**0.9096**	0.8924
3	**0.8633**	0.7997	**0.9545**	0.9221	**0.9150**	0.8687
4	**0.8760**	0.7972	**0.9456**	0.8976	**0.9170**	0.8526
5	**0.8793**	0.7829	**0.9442**	0.8766	**0.9195**	0.8424
Image	Butterfly		Cameraman		Lena	
	Or: 0.8741		Or: 0.8941		Or: 0.9058	
T_i	ABM-Seg	Otsu	ABM-Seg	Otsu	ABM-Seg	Otsu
2	**0.9428**	0.9243	**0.9450**	0.9372	**0.9540**	0.9432
3	**0.9446**	0.9105	**0.9470**	0.9245	**0.9502**	0.9258
4	**0.9455**	0.9082	**0.9388**	0.8960	**0.9484**	0.9195
5	**0.9335**	0.8675	**0.9451**	0.9112	**0.9525**	0.9220

Or: Homogeneity index of original image, **ABM-Seg**: Homogeneity index of the segmented image using an ABM-Seg, **Otsu**: Homogeneity index of the segmented image using an Otsu method.

Otsu method presents missing or incomplete parts. Overall, these observations indicate that the ABM-Seg algorithm is a more accurate and effective method for image segmentation as compared to the Otsu method. By producing boundaries that match the true edges of objects and presenting a lower number of inaccuracies and artifacts, the ABM-Seg algorithm allows for the more precise and comprehensive segmentation of images.

In conclusion, the results of the experiments clearly indicate that the ABM-Seg approach outperforms the Otsu method in terms of segmentation quality. The ABM-Seg approach produces more homogeneous regions, with a low presence of artifacts or noise elements, and preserves the important features of the image. These advantages make the ABM-Seg approach a more reliable and accurate approach for image segmentation.

2) NUMERICAL EVALUATION

This part compares numerically the segmentation results of the ABM-Seg method with those of the Otsu method using the homogeneity index. The results are presented in Table 1, which shows the homogeneity values for each method across the images presented in Figures 6-11. The homogeneity index is a metric used to evaluate the quality of segmentation results, where higher values indicate more homogeneous regions. In this case, the homogeneity values indicate how well the segmentation methods are able to identify the regions of interest in the images while preserving their characteristics.

An analysis of Table 1 indicates that the ABM-Seg method obtains the best values of homogeneity for all images, compared to the Otsu method. This suggests that the ABM-Seg method is more effective in accurately detecting the regions of interest in the images, without removing important features.

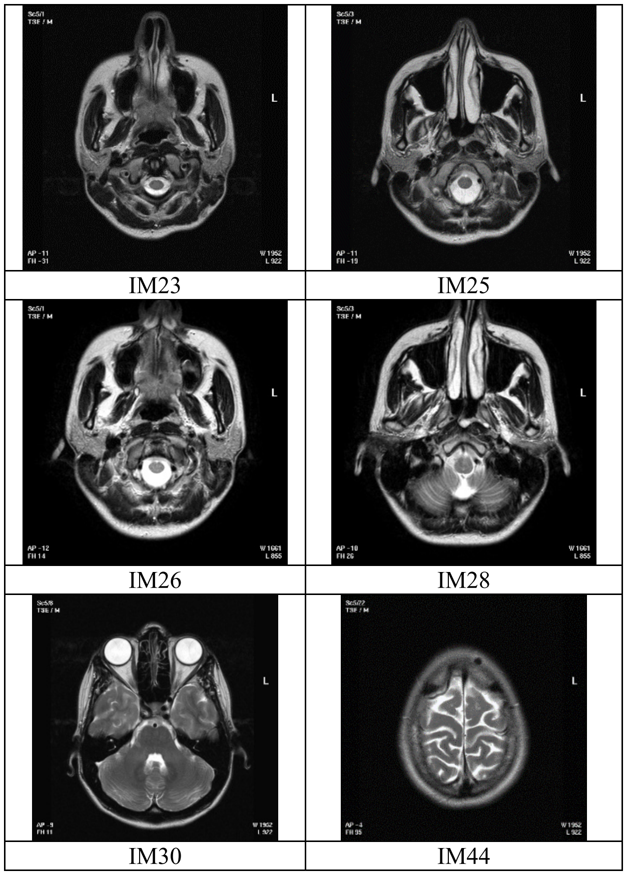


FIGURE 12. MRI images used in the experiments.

The results also show that the Otsu method's performance degrades as the number of thresholds increases. This is because the method is not able to consistently produce regions as the number of thresholds increases. This highlights the limitation of the Otsu method in producing consistent and accurate segmentation results.

Overall, the results suggest that the proposed ABM-Seg method is more effective in producing accurate segmentation results compared to the Otsu method, particularly in preserving the characteristics of the regions of interest in the images. This is an important contribution, as accurate segmentation results are essential for many applications. These findings suggest that the use of local features in image segmentation approaches can significantly improve the accuracy and precision of the homogenization process. Overall, our results highlight the importance of considering local features in image processing methods to obtain more accurate and detailed segmentation results.

C. ABM-SEG COMPARED WITH AN HOMOGENIZATION APPROACH

In the third subsection, the proposed method is compared with the state-of-the-art homogenization approach proposed in [25] (MED-MOR), which combines a median filter with a set of morphological operations. Similar to our scheme,

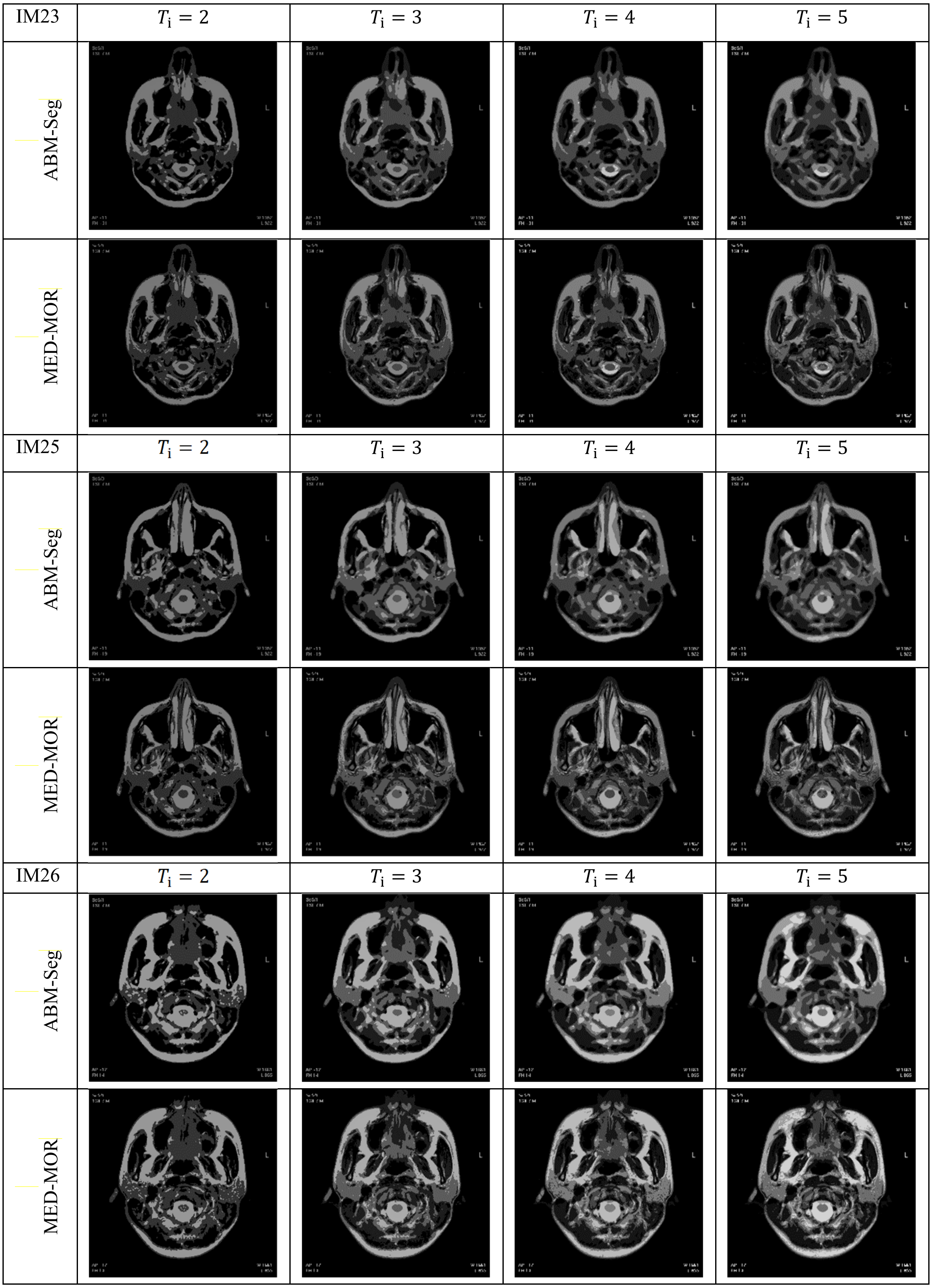


FIGURE 13. **Segmentation results evaluated over the images IM23, IM25 and IM26.**

this algorithm integrates the homogenization technique with Otsu's method. Because this scheme was designed to segment MRI images, all experiments were conducted using this type of image.

To analyze the quantitative and qualitative results in detail, a set of six representative images was selected. These images are presented in Fig. 12. All selected images were considered special cases owing to their complexity.

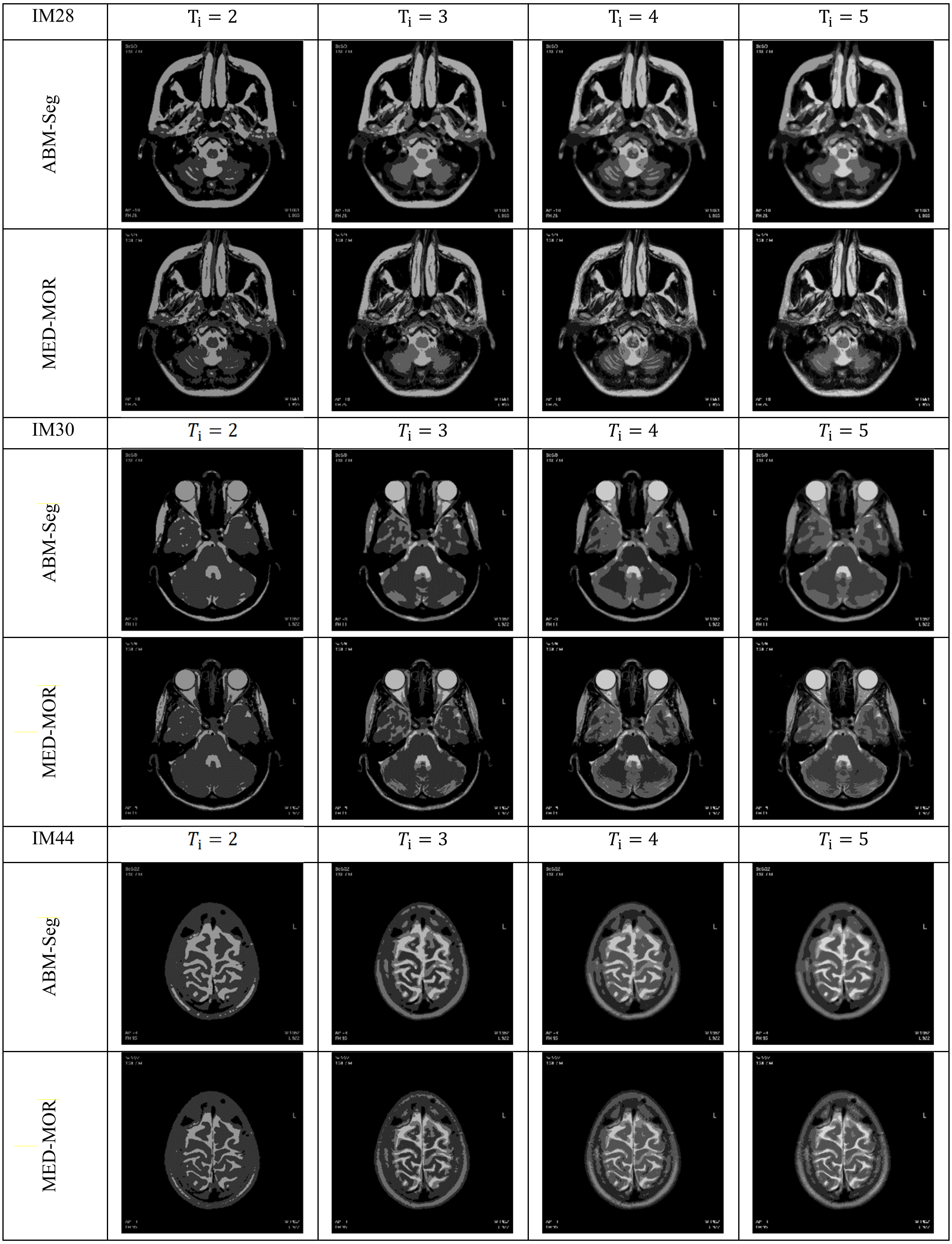


FIGURE 14. Segmentation results evaluated over the images IM28, IM30 and IM44.

Figures 13 and 14 present the qualitative results for different threshold values, $T_i = \{2, 3, 4, 5\}$, between both algorithms, considering the images from Figure 12. When evaluating the segmentation results in images, several characteristics are visually evaluated to determine if the segmentation has been successful. These characteristics are particularly important, as they reflect the impact of the homogenization process.

An analysis of Figures 13 and 14 indicates that ABM-Seg produces sharper edges around the elements, with less over- or under-smoothing, which means that the objects are better delineated. In addition, the boundaries between the objects are more precise, and there are fewer artifacts or discontinuities in the segmented image. Moreover, the details of the objects were well preserved in the segmentation results obtained using the ABM-Seg algorithm. In contrast, the segmentation result obtained with MED-MOR showed a significant loss of detail in the edges and contours of the objects. Segmentation is less precise and there are more artifacts and discontinuities in the segmented image. Moreover, the edges are smoother, which leads to the loss of some object detail. Under such conditions, it is clear that the ABM-Seg method captures more details and edges of the objects than the MED-MOR algorithm, resulting in more precise segmentation boundaries. Our approach also preserved finer details of the elements, resulting in a more natural and realistic appearance. It is also evident that the ABM-Seg scheme effectively reduces noise in the image without introducing new artifacts. Figures 13 and 14 show that the MED-MOR method is not always able to effectively handle complex structures or noise that is present in the image. Consequently, this method introduces unwanted artifacts when the noise structure is larger than the morphological filter (5×5).

TABLE 2. Homogeneity (H) values from Figures 13 and 14.

Image	IM_00023		IM_00025		IM_00026	
	Or: 0.9452		Or: 0.9365		Or: 0.9237	
T_i	ABM-Seg	MED-MOR	ABM-Seg	MED-MOR	ABM-Seg	MED-MOR
2	**0.9785**	**0.9776**	**0.9760**	0.9751	**0.9734**	0.9720
3	**0.9788**	0.9757	**0.9714**	0.9667	**0.9738**	0.9707
4	**0.9799**	0.9765	**0.9738**	0.9668	**0.9692**	0.9621
5	**0.9748**	0.9674	**0.9705**	0.9606	**0.9656**	0.9556
Image	IM_00028		IM_00030		IM_00044	
	Or: 0.9170		Or: 0.9451		Or: 0.9668	
T_i	ABM-Seg	MED-MOR	ABM-Seg	MED-MOR	ABM-Seg	MED-MOR
2	**0.9716**	0.9700	**0.9808**	0.9801	**0.9890**	0.9888
3	**0.9651**	0.9594	**0.9757**	0.9718	**0.9828**	0.9827
4	**0.9663**	0.9575	**0.9735**	0.9670	**0.9814**	0.9800
5	**0.9630**	0.9504	**0.9746**	0.9667	**0.9806**	0.9776

Or: Homogeneity index of original image, **ABM-Seg**: Homogeneity index of the segmented image using ABM-Seg, **MED-MOR**: Homogeneity index of the segmented image using the MED-MOR scheme.

Table 2 presents the quantitative comparison results between the ABM-Seg and MED-MOR algorithms for the images shown in Figures 13 and 14. The Table reports the homogenization index, which evaluates how well the algorithm can remove noise and produce homogenous regions in the image. Higher values of the homogenization index indicate better performance. It is evident from the table that the ABM-Seg algorithm performs better than the MED-MOR algorithm because it has a higher homogenization index for all images.

The results of these experiments demonstrate that the rules incorporated in the proposed agent-based model are highly effective for processing local information in image segmentation. The pixel interactions among the neighboring elements characterized in the model enable the generation of homogeneous regions that preserve the essential details while simultaneously eliminating the noise elements or inconsistent information. The remarkable results of the agent-based model are a consequence of its iterative process. Under this mechanism, the model continually improves its homogenization results with each iteration. The model can take into account the results of the previous iteration to adjust and refine the results considering the rules used for pixel interactions among neighbor elements. This can lead to more accurate and precise homogenization results with less over-smoothing or under-smoothing of the image regions. On the other hand, the MED-MOR method is less flexible than the ABM-Seg scheme because it uses fixed filters that cannot be adapted to the specific characteristics of each noise structure. As a result, this approach may not be able to completely eliminate noise from the image, leaving artifacts behind due to partial elimination. The lack of adaptability to local features and variations is a major limitation of this approach.

VI. CONCLUSION

The article describes the use of agent-based modeling (ABM) as a homogenization method for image segmentation. Our approach involves associating the attributes and behaviors of agents with the pixels of an image and their relative differences. Each agent makes decisions based on a set of rules that determine its behavior based on its differences from other neighboring elements. The intensity value of each agent is then incremented or decremented based on the most common sign among its neighbors as a rule of behavior. This process is repeated in each iteration, modifying the intensity values of all agents to homogenize their local regions to the same intensity value.

Our agent-based method for image homogenization uses local features to capture detailed information about image regions, which makes it less sensitive to outliers or extreme values in the image. This results in more accurate and precise homogenization, with less oversmoothing or undersmoothing of image regions, compared to other approaches that rely on global characteristics. The iterative process of the agent-based model can also be one of the reasons behind its outstanding performance. With each iteration, the model enhances its homogenization outcomes, taking into consideration the rules used for pixel interactions among neighboring elements, and using the previous iteration's results to adjust and refine the outcomes. This continual improvement can result in more precise and accurate homogenization results.

Experimental tests were conducted using a representative set of images. The homogeneity of the segmentations is considered the main evaluation criterion. The comparison considers two important aspects: Visual and numerical. The visual comparison involves the visual evaluation of a set of images to determine the quality of the segmentation results. The second aspect of the comparison involves a numerical comparison of the homogeneity index among different images. In this study, a homogeneity index H was proposed based on a gray-level co-occurrence matrix (GLCM). The proposed homogeneity index, H, can appropriately determine the homogeneity of the segmentation results.

The results of the experiments indicate that the ABM-Seg technique is more successful than the Otsu method and the MED-MOR scheme in achieving precise segmentation outcomes, particularly in maintaining the distinctive features of the image's regions of interest. This is a valuable finding because accurate segmentation outcomes are crucial for numerous applications.

One direction that deserves further research is to include in the agent-based model rules that involve not only local pixels but also elements of distant positions. Under such conditions, it can be possible to combine local and global features to improve the performance of the homogenization approach.

REFERENCES

[1] X. Zhu, K. Guo, H. Fang, L. Chen, S. Ren, and B. Hu, "Cross view capture for stereo image super-resolution," *IEEE Trans. Multimedia*, vol. 24, pp. 3074–3086, 2022.

[2] X. Zhu, K. Guo, S. Ren, B. Hu, M. Hu, and H. Fang, "Lightweight image super-resolution with expectation-maximization attention mechanism," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 32, no. 3, pp. 1273–1284, Mar. 2022.

[3] G. Gavidia, M. Cerrolaza, E. Oñate, E. Soudah, and J. Pérez, "Desarrollo de una herramienta de procesamiento de imágenes médicas en MATLAB y su integración en medical GiD," Int. Centre Numer. Methods Eng. (CIMNE), Venezuela, Tech. Rep., 2017.

[4] Y. Huerfano et al., "Métodos de segmentación de imágenes cardiacas: Fundamentos y alcance," *Revista Latinoamericana de Hipertensión*, vol. 10, no. 3, pp. 61–71, 2015.

[5] N. la Serna and U. Róman, "Técnicas de segmentación en procesamiento digital de imágenes," *Revista de Ingeniería de Sistemas e Informática*, vol. 6, no. 2, pp. 9–16, 2009.

[6] N. R. Pal and S. K. Pal, "A review on image segmentation techniques," *Pattern Recognit.*, vol. 26, no. 9, pp. 1277–1294, Sep. 1993.

[7] D. Kaur and Y. Kaur, "Various image segmentation techniques: A review," *Int. J. Comput. Sci. Mobile Comput.*, vol. 3, no. 5, pp. 809–814, 2014.

[8] C. Li, C. Xu, C. Gui, and M. D. Fox, "Distance regularized level set evolution and its application to image segmentation," *IEEE Trans. Image Process.*, vol. 19, no. 12, pp. 3243–3254, Dec. 2010.

[9] C. Li, R. Huang, Z. Ding, J. C. Gatenby, D. N. Metaxas, and J. C. Gore, "A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI," *IEEE Trans. Image Process.*, vol. 20, no. 7, pp. 2007–2016, Jul. 2011.

[10] A. Janwale, "Plant leaves image segmentation techniques: A review," *Int. J. Comput. Sci. Eng.*, vol. 5, pp. 147–150, Jun. 2017.

[11] S. Yuheng and Y. Hao, "Image segmentation algorithms overview," 2017, *arXiv:1707.02051*.

[12] K. K. D. Ramesh, G. Kumar, K. Swapna, D. Datta, and S. Rajest, "A review of medical image segmentation algorithms," *EAI Endorsed Trans. Pervasive Health Technol.*, vol. 7, no. 27, Jul. 2018, Art. no. 169184, doi: 10.4108/EAI.12-4-2021.169184.

[13] X. Jiang, R. Zhang, and S. Nie, "Image segmentation based on PDEs model: A survey," in *Proc. 3rd Int. Conf. Bioinf. Biomed. Eng.*, Jun. 2009, pp. 1–4, doi: 10.1109/ICBBE.2009.5162922.

[14] M. Jogin, Mohana, M. S. Madhulika, G. D. Divya, R. K. Meghana, and S. Apoorva, "Feature extraction using convolution neural networks (CNN) and deep learning," in *Proc. 3rd IEEE Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT)*, May 2018, pp. 2319–2323, doi: 10.1109/RTEICT42901.2018.9012507.

[15] J. Fang, H. Liu, L. Zhang, J. Liu, and H. Liu, "Fuzzy region-based active contours driven by weighting global and local fitting energy," *IEEE Access*, vol. 7, pp. 184518–184536, 2019.

[16] N. Otsu, "A threshold selection method from gray-level histogram," *IEEE Trans. Syst. Sci. Cybern.*, vol. SSC-9, no. 1, pp. 62–66, Jan. 1979.

[17] M. H. Merzban and M. Elbayoumi, "Efficient solution of Otsu multilevel image thresholding: A comparative study," *Expert Syst. Appl.*, vol. 116, pp. 299–309, Feb. 2019.

[18] M. Huang, W. Yu, and D. Zhu, "An improved image segmentation algorithm based on the Otsu method," in *Proc. 13th ACIS Int. Conf. Softw. Eng. Artif. Intell., Netw. Parallel/Distrib. Comput.*, vol. 13, Aug. 2012, pp. 135–139.

[19] C. Huang, X. Li, and Y. Wen, "AN Otsu image segmentation based on fruitfly optimization algorithm," *Alexandria Eng. J.*, vol. 60, no. 1, pp. 183–188, Feb. 2021.

[20] X. Xu, S. Xu, L. Jin, and E. Song, "Characteristic analysis of Otsu threshold and its applications," *Pattern Recognit. Lett.*, vol. 32, no. 7, pp. 956–961, May 2011.

[21] Z. Qu and L. Zhang, "Research on image segmentation based on the improved Otsu algorithm," in *Proc. 2nd Int. Conf. Intell. Hum.-Mach. Syst. Cybern.*, Aug. 2010, pp. 228–231.

[22] Y. Lou, T. Zeng, S. Osher, and J. Xin, "A weighted difference of anisotropic and isotropic total variation model for image processing," *SIAM J. Imag. Sci.*, vol. 8, no. 3, pp. 1798–1823, Jan. 2015.

[23] L. Lu, Y. Zhou, K. Panetta, and S. Agaian, "Comparative study of histogram equalization algorithms for image enhancement," *Proc. SPIE*, vol. 7708, pp. 337–347, Apr. 2010.

[24] R. J. Jebadass and P. Balasubramaniam, "Low contrast enhancement technique for color images using interval-valued intuitionistic fuzzy sets with contrast limited adaptive histogram equalization," *Soft Comput.*, vol. 26, no. 10, pp. 1960–4949, 2022.

[25] M. Nyo, F. Mebarek-Oudina, S. Hlaing, and N. Khan, "Otsu's thresholding technique for MRI image brain tumor segmentation," *Multimedia Tools Appl.*, vol. 81, no. 30, pp. 43837–43849, Dec. 2022.

[26] J.-P. Treuil, A. Drogoul, and J.-D. Zucker, "Modélisation et simulation à base d'agents: Exemples commentés, outils informatiques et questions theéoriques," Univ. Paris, Paris, France, Tech. Rep. 1077, 2008, p. 322.

[27] J. Epstein and R. Axtell, *Growing Artificial Societies Social Science From the Bottom Up*. Washington, DC, USA: MIT Press, 1996.

[28] A. K. Chavali, E. P. Gianchandani, K. S. Tung, M. B. Lawrence, S. M. Peirce, and J. A. Papin, "Characterizing emergent properties of immunological systems with multi-cellular rule-based computational modeling," *Trends Immunol.*, vol. 29, no. 12, pp. 589–599, Dec. 2008.

[29] L. Rodríguez and P. Roggero, "Modelos basados en agentes: Aportes epistemológicos y teóricos para la investigación social," *Revista Mexicana de Ciencias Políticas y Sociales*, vol. 225, pp. 233–266, Mar. 2015.

[30] T. C. Schelling, "Models of segregation," *Amer. Econ. Rev.*, vol. 59, no. 2, pp. 488–493, 1969.

[31] M. Jahanbani, M. H. Vahidnia, and M. Aspanani, "Geographical agent-based modeling and satellite image processing with application to facilitate the exploration of minerals in behshahr, Iran," *Arabian J. Geosci.*, vol. 15, no. 9, p. 901, May 2022.

[32] A. Hussein, M. Salman, H. Essa, and N. Hussein, "Developing agent-based model for colorization," *J. Univ. Babylon Pure Appl. Sci.*, vol. 28, no. 1, pp. 147–157, 2020.

[33] E. Young and B. Aguirre, "PrioritEvac: An agent-based model (ABM) for examining social factors of building fire evacuation," *Inf. Syst. Frontiers*, vol. 23, no. 5, pp. 1083–1096, Sep. 2021.

[34] E. Frias-Martinez, G. Williamson, and V. Frias-Martinez, "An agent-based model of epidemic spread using human mobility and social network information," in *Proc. IEEE 3rd Int. Conf. Privacy, Secur., Risk Trust IEEE 3rd Int. Conf. Social Comput.*, Oct. 2011, pp. 57–64.

[35] L. Zhuo and D. Han, "Agent-based modelling and flood risk management: A compendious literature review," *J. Hydrol.*, vol. 591, Dec. 2020, Art. no. 125600.

[36] P. Johnson, S. Nicholls, J. Student, B. Amelung, R. Baggio, S. Balbi, I. Boavida-Portugal, E. de Jong, G. J. Hofstede, M. Lamers, M. Pons, and R. Steiger, "Easing the adoption of agent-based modelling (ABM) in tourism research," *Current Issues Tourism*, vol. 20, no. 8, pp. 801–808, Jun. 2017.

[37] A. Hulme, S. Mclean, P. M. Salmon, J. Thompson, B. R. Lane, and R. O. Nielsen, "Computational methods to model complex systems in sports injury research: Agent-based modelling (ABM) and systems dynamics (SD) modelling," *Brit. J. Sports Med.*, vol. 53, no. 24, pp. 1507–1510, Dec. 2019.

[38] S. de Marchi and S. E. Page, "Agent-based models," *Annu. Rev. Political Sci.*, vol. 17, no. 1, pp. 1–20, May 2014.

[39] S. C. Bankes, "Agent-based modeling: A revolution?" *Proc. Nat. Acad. Sci. USA*, vol. 99, no. 3, pp. 7199–7200, May 2002, doi: 10.1073/PNAS.072081299.

[40] A. T. H. Al-Rahlawee and J. Rahebi, "Multilevel thresholding of images with improved Otsu thresholding by black widow optimization algorithm," *Multimedia Tools Appl.*, vol. 80, no. 18, pp. 28217–28243, Jun. 2021.

[41] Y. Niloofar and A. Morteza, "A survey of performance evaluation metrics for image segmentation," *J. Electron. Imag.*, vol. 29, no. 1, 2020, Art. no. 010901.

[42] O. Timo, P. Matti, and M. Topi, "Texture features for image classification," *Pattern Recognit*, vol. 33, no. 2, pp. 341–352, 2002.

[43] R. M. Haralick and L. G. Shapiro, "3D gray level co-occurrence matrix based classification of favor benign and borderline types in follicular neoplasm images," in *Computer and Robot Vision*, vol. 1. Reading, MA, USA: Addison-Wesley, 1992.

[44] M. Presutti, "La matriz de co-ocurrencia en la clasificación multiespectral: Tutorial para la enseñanza de medidas texturales en cursos de grado universitario," in *Proc. 4a Jornada de Educação em Sensoriamento Remoto no Âmbito do Mercosul*, Aug. 2004, pp. 1–8.

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