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An improved active contour model for food image segmentation

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Abstract

Active contour (snake) segmentation is extensively used in image processing and analysis applications, particularly for identifying object boundaries. This method is adopted for food image segmentation, wherein the boundaries of the foods in an image are the objects of interest. In this research, a region-based active contour, which is regarded as an energy-minimizing process, is used for image segmentation. Additionally, a modified active contour method is presented in this paper using the artificial bee colony (ABC) algorithm to optimize the weights of the external energy function in the original active contour (AC) method. A stopping criterion is also introduced to the AC method, wherein the snake movement of the contour will cease after a certain number of unimproved snake movements. The food image dataset was collected manually for this research; it comprises 102 images of different food types and positions within each image. The modified active contour method demonstrated significant improvements in fewer iterations and segmentation quality compared with the original method.

Keywords: Active contour, Artificial bee colony, Food image, Identification, Segmentation, Snake.

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1. Introduction

Nowadays, food image segmentation methods have a significant influence on the applications of dietary assessments. These assessments are useful for individuals with diet-related chronic diseases, aiding in management or treatment through computer vision systems. These systems are employed to detect and recognize various foods and their portions in images.

Therefore, they primarily rely on image segmentation methods to differentiate various types of foods in food images [1]. Moreover, the existing solutions assume the number, color, and shape of dishes in an image, as well as the possible number of food items in each dish and the visual properties of the background, to address the automatic food detection and segmentation problems. This study focuses on single-dish foods and the segmentation of food portions within the dish. Herein, the food detection and contour initialization processes are also automatically executed.

However, active contour (snake) segmentation is used extensively in image processing and analysis applications, particularly for identifying object boundaries. Active contour is an energy-minimizing process where an initial spline is placed on an image and is guided by external constraints, which are gradually influenced by the image structure, and pull the spline to the object's features, such as lines and edges. The energy minimization process is based on an energy function that calculates the internal and external energy of the initial contour. By minimizing this energy value, the active contour technique guides the initial contour toward the contour of the object of interest in an image. Moreover, active contour models have two types, namely, boundary-based active contours [2] that categorize the object based on contours only and region-based active contours [3] that also uses the internal and external regions of the contour for the segmentation process. This study considered the region-based active contour to ensure substantially accurate segmentation of food images. Recently, many applications have been developed for food image segmentation, wherein AC is one of the techniques utilized for this application. However, this method has several drawbacks associated with the food image itself, thereby preventing the snakes from accurately locating the object's boundaries. One of the issues affecting the snakes' performance is the initial contour, which can lead to the misallocation of some objects, as well as non-food objects such as plates, food containers, or other utensils that are often not detected; this contour reduces the accuracy of food identification. To address these issues in food segmentation using the AC (snake) method, several techniques have been introduced and implemented in this research during the preprocessing step of food images. Additionally, the active contour method was improved by introducing an artificial bee colony (ABC) algorithm to optimize the energy minimization step of the original active contour. The quality of the food segmentation results was then evaluated using four metrics: precision, recall, similarity index (SI), and Tanimoto coefficient (TC).

2. Related Work

Since the introduction of the parametric active contour by Kass, et al. [2], a number of research works have been conducted considering different aspects of active models. Thus, various active model representations, such as finite-element models [4], spline-based models [5], and Fourier descriptor–based models exist [6]. Moreover, different external forces were introduced to improve the classical active contour model, and two types of external forces, that is, inflation force (referred to as balloon) and gradient vector flow field (GVF), were presented in [7]. GVFs are dense vector fields derived from an image by minimizing the energy functional in a variational framework to increase the capture range, thus overcoming the contour initialization issue. GVF is regarded as one of the first successful approaches in active contour segmentation, which has been improved later. Other GVF-based approaches are vector field convolution [8] and the sparse field method, which is the most recent [9]. Meanwhile, another productive approach uses the snake energy minimization mechanism by applying other optimization search methods, such as dynamic programming [10], greedy algorithms [11], genetic algorithms [12] and swarm-based optimization algorithms [13]. This approach primarily aims to optimize the snake's external energy function [Section 3, Eq. (3)] by applying optimization search algorithms. Furthermore, the snake and its variants have been adopted for various types of applications, such as random object segmentation [13-16], and mostly for medical image segmentation [17-22].

Meanwhile, various methods, including active contour, have been used for food image segmentation and have primarily been proposed for dietary assessment applications. In Shroff et al. [23], a simple adaptive threshold method was applied to a simplified food image, where the plate is white and all foods are clearly separated.. In He et al. [24], three types of image segmentation methods were adopted, namely, active contours, normalized cuts, and local variation, on food images. The results indicated that local variation is superior among the three. In the local variation method, many dishes were used, and the background was regarded as the pixels of the most frequent color. The authors of [23] applied the contour detection method to food images by combining location and segmentation heuristics. Furthermore, the mean-shift filtering in the CIELAB color space method was proposed in Anthimopoulos, et al. [24] to segment the food inside a given dish. In Chen et al. [27], the active contour method was also adopted with the aid of a food saliency map to segment the food in an image after detecting the food on a plate. other image segmentation approaches were also utilized in applications of dietary assessments, which are based on classification schemes trained on food images, to improve the segmentation process [25-29]. Recently, in Dehais et al. [32], a method was proposed to combine the region growing/merging techniques with a deep convolutional neural network (CNN)-based food border map for food border detection, where this CNN-based map was used to guide the region growing/merging technique. However, this method is only employed for already detected dishes in an image. The results showed a significant improvement in segmentation performance after using the CNN-based map.

3. Snake Image Segmentation

The function of the snakes or active contour is to iteratively minimize the segmentation energy, where the initial contour is proposed on the food image, and then the minimized energy is used to deform the contour on the boundary of the objects of interest in an image. Two energy types (i.e., internal and external) are often calculated in the active contour methods. When the segmentation energy function reaches a unique global minimum value, the snake contour becomes the same as the edges of the object of interest. Deformation of snakes is performed by minimizing the energy function (E_{snake}), as expressed in the following equation:

$$E_{\text{snake}} = \int_0^1 E_{\text{snake}}\left(p(s)\right) ds = \int_0^1 \left(E_{\text{internal}}\left(p(s)\right) + E_{\text{external}}\left(p(s)\right)\right) ds. \quad (1)$$

The first energy component is based on the contour shape, whereas the second energy component depends on the image intensity.

$$E_{\text{internal}} = \frac{1}{2}\left(\alpha(s)\left|\frac{\partial p(s)}{\partial s}\right|^2 + \beta(s)\left|\frac{\partial p(s)}{\partial s}\right|^2\right). \quad (2)$$

The first- and second-order derivatives of $p(s)$ are the terms of the internal energy. In addition, $\alpha(s)$ and $\beta(s)$ denote the snake's tension and rigidity properties, respectively.

$$E_{\text{external}} = W_{\text{line}}E_{\text{line}} + W_{\text{edge}}E_{\text{edge}} + W_{\text{term}}E_{\text{term}}. \quad (3)$$

The external energy term is a linear combination of three components that are derived from the image properties as follows:

$$E_{\text{line}} = I(x,y), \quad (4)$$
$$E_{\text{edge}} = -(G_\sigma * \nabla^2 I)^2, \quad (5)$$
$$E_{\text{term}} = \frac{C_{yy}C_x^2 - C_{xy}C_xC_y + C_{xx}C_y^2}{(C_x^2 + C_y^2)^{\frac{3}{2}}}, \quad (6)$$

where the line energy E_{line} is the image intensity $I(x,y)$ and the edge energy E_{edge} is computed using a Gaussian with a standard deviation σ and the gradient operator ∇. Meanwhile, the termination energy E_{term} is obtained from the curvature of the contour's level $C(x,y)$. However, each control point can be updated by iteratively using a gradient descent method as follows:

$$\vec{x}_t = (A - \gamma I)^{-1}\left(\gamma \vec{x}_{t-1} - \vec{h}_x\left(\vec{x}_{t-1}, \vec{y}_{t-1}\right)\right) \quad (7)$$
$$\vec{y}_t = (A - \gamma I)^{-1}\left(\gamma \vec{y}_{t-1} - \vec{h}_y\left(\vec{x}_{t-1}, \vec{y}_{t-1}\right)\right), \quad (8)$$

where A is a Penta diagonal matrix that contains numerical coefficients to the descent internal energy gradient [30].

However, this type of active contour model has a significant issue because it strongly depends on the energy weights illustrated earlier. This indicates that a weight optimization method should be applied to improve this active contour (snake) model. In this work, a metaheuristic optimization framework is employed using the ABC algorithm for active contour external energy weight optimization. The ABC algorithm is used to optimize the weight parameters in Equation 3 and to automatically search for the global optimal values to be used in the external energy equation.

4. Overview of the ABC Algorithm

ABC is one of the most attractive swarm intelligence algorithms, which has demonstrated its efficiency and proven its powerful performance in many research fields [31-33]. The ABC algorithm is a metaheuristic-based algorithm inspired by the foraging behavior of bees in nature [34]. The foraging bee concept is one of the most attractive methods that have inspired researchers in the computer science field to apply and adapt heuristic techniques based on the swarm, mating, and foraging behaviors of honey bees [35]. ABC was proposed by Karaboga [36] in this algorithm, bees are categorized into three types: employed bees, onlookers, and scouts. The colony is divided equally between employed and onlooker bees, with each group comprising 50% of the total bees. The number of food sources corresponds to the number of bees, meaning the solutions are equivalent to the combined total of employed and onlooker bees. The primary phases in the Artificial Bee Colony (ABC) algorithm are EmployedBee and OnlookerBee. Initially, employed bees are dispatched to evaluate the nectar amount in food sources within the search space and explore around these sources. Subsequently, onlooker bees search near the best food sources based on information provided by employed bees. When employed bees reach their visitation limit for a food source, they transform into scout bees. The main steps of the algorithm are as follows:

- Initialize.
- Repeat.

(a) Send the employed bees to the food sources in the search space, and the bees will determine the nectar amount of the sources.

(b) Send the onlooker bees to the food sources in the search space, and the bees will determine the nectar amount of the sources.

(c) Send the scouts to the search space to discover a new food source.

(d) Memorize the excellent food sources found so far.

- UNTIL Requirements Are Met.

In the ABC algorithm, the search is initiated by sending the employed bees to the food sources, which calculate the amount of nectar in the sources. The onlooker bees are then sent to measure the nectar of the food sources after obtaining information on the nectar amount of the excellent food sources. These two phases are responsible for the local search process of the algorithm. The scout bees are determined after the food sources are exhausted by the employed and onlooker bees.

Moreover, the food source in the ABC algorithm represents a potential solution to the problem. Food source initialization is randomly facilitated, and the amount of nectar in each food source is determined based on the food source quality corresponding to the vicinity of the solution. The employed bees explore the search space to identify precise and high-quality solutions. Subsequently, the bees gather this information and return to the hive, where they share it with other bees, known as onlooker bees. Based on the quality of the solutions, onlooker bees are directed to visit the best solutions using a "roulette wheel selection" method. These bees then assess the food source's quality and search neighboring areas. A greedy selection method is employed to choose between the current and neighboring solutions, retaining those with higher quality values and discarding poorer ones. If a solution representing a food source is visited by employed and onlooker bees a certain number of times (referred to as the "limit") without any improvement, the employed bees abandon that food source and transform into scout bees. The scout bees are then sent to search randomly for new food sources. The "limit" parameter is critically important to ensure the global search capability of the algorithm.

In the ABC algorithm, each food source position represents a possible solution to the optimization problem. Each solution to the optimization problem is associated with a fitness value, which measures the amount of nectar. The number of food sources (i.e., solutions) in the population is equal to the number of bees. The ABC generates the N population size of random solutions in the initial stage, where N denotes the total number of food sources around the hive. Thus, each solution represents a position of one food source. denoted by X_{ij} (where i is a particular solution, i = 1, 2, …, N), and each solution is a D-dimensional vector (where j is its dimension, j = 1, 2, …, D).

As a natural foraging behavior, the bees search for a food source in a maximized search manner. The maximization problem aims to determine the maximum of the objective function $F(X)$, where $X_i \in N$. X_i denotes the position of the ith food source and $F(X_i)$ It is the amount of nectar in a certain food source.

After all the employed bees complete the search process, they share the nectar information of food sources (solutions) and their position information with the onlooker bees. Then, the onlooker bees choose a food source based on the probability value Pi associated with the food source. The probability value for each food source is calculated using the following equation:

$$Pi = \frac{F(X_i)}{\sum_{l=1}^{N} F(X_l)}. \tag{9}$$

The onlooker bees then use this probability value to determine which food source (X_i) they will visit next. Food sources (solutions) with a high probability might be visited more than once, and the neighboring solutions are checked as well. The position of the neighboring solution is calculated using the following equation:

$$X_{i(j+1)} = X_{ij} + \beta\left(X_{ij} - X_{kj}\right). \tag{10}$$

Moreover, the pseudocode of the original ABC algorithm is presented in Figure 1.

Initialization Phase
1: Initialize the population of food sources x_{ij}, I = 1,…,SN using Equation (11).
2: Evaluate the nectar amount in each food source in the population.
3: Initiate the food sources with EmployedBees.
4: Cycle = 1
5: ***Repeat***
EmpolyedBee Phase
6: For each EmployedBee, find a neighbor food source using Equation (10).
7: Evaluate the nectar amount of the new neighbor food source v_{ij}.
8: Apply a greedy selection between the two neighbor food sources x_{ij}, v_{ij}.
OnlookerBee Phase
9: Calculate the probability values pi for each food source x_{ij} from the EmployedBee phase using Equation (9).
10: For each OnlookerBee, find a neighbor food source v_{ij} using Equation (10).
11: Evaluate the nectar amount of the new neighbor food source v_{ij}.
12: Apply a greedy selection between the two neighbor food sources x_{ij}, v_{ij}.
ScoutBee Phase
13: Determine the abandoned food source from the food source population if exists, and then replace it with new random food source v_{ij} using Equation (11).
14: Memorize the excellent food source found so far.
15: Cycle = Cycle+1.
16: ***Until*** *Cycle = MCN* (maximum cycle number).

Figure 1.
Original pseudocode of the ABC algorithm.

Here, i represents a particular food source position (i = 1, 2, …, N) and k denotes a randomly selected neighbor position (k = 1, 2, …, N) whose value is different from the i value. β is a random number between [−1, 1], which is used to estimate the neighboring food sources around X_{ij}. The smaller the difference between the two parameters (X_{ij}, X_{kj}), the smaller the change that appears on the X_{ij} value. If the fitness of the new solution (food source) is better, then this solution will replace the old one in memory. Otherwise, the old position will remain. The solution with unimproved fitness is abandoned after a certain number of trials, and scout bees are sent to discover a new solution according to the algorithm to Equation11. Then, the new solution found by the scout bees replaces the abandoned one [36].

$$X_{ij} = X_{ij} + \text{rand}[0,1]\left(X_{j\max} - X_{j\min}\right). \tag{11}$$

For the improvement of the active contour method, the food source for the algorithm will be the list of the weight parameter in Equation 3 (Section 3), where each source (solution) is composed of the proposed values of the parameters W_{line}, W_{edge}, and W_{term}. Therefore, the objective of the ABC algorithm is to determine the global optimal set of values for these parameters, in which the energy function E_{snake} in Eq. (1) (Section 3) is minimized.

5. Image Preprocessing

In this research, we used 102 food images captured with a mobile phone camera for experimental testing. However, these images required some preprocessing before being used for the active contour segmentation process. Several preprocessing steps were employed in this study, each serving a specific purpose to address various drawbacks of the active contour method and to enhance the overall performance of the snake algorithm. These steps are as follows:

a. Reshape the images (resize) to reduce the segmentation time.
b. Perform a background removal process to identify the area of segmentation interest (initial contour).
c. Perform a simple object detection method to remove the shadow and identify the initial contour.
d. Filter the images for smoothing purposes.

The first problem with these images was their size or resolution; some of them had a high resolution, while others had a low resolution. Therefore, we suggested reducing the image size or reshaping the image by utilizing the image resize function in MATLAB with a scale of 0.1. This process also reduces the segmentation time. Figure 2 illustrates the reshaping process.

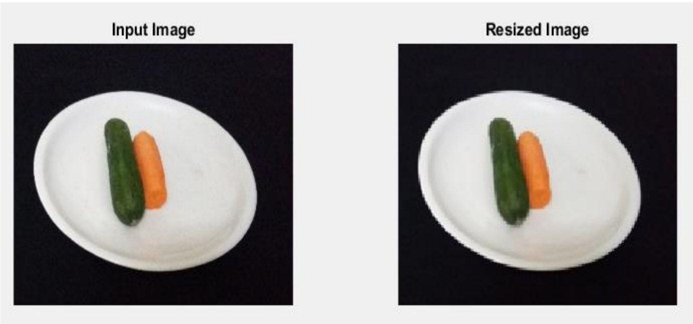

Figure 2.
Images of the reshaping process.

The next step in the image preprocessing stage was to develop a practical approach for the contour initialization process, which is considered one of the issues affecting the performance of the active contour (snake) method. In this step, a background removal method was applied as a preliminary measure to distinguish the plate on which the food is placed from the background behind the food plate, as shown in Figure 3.

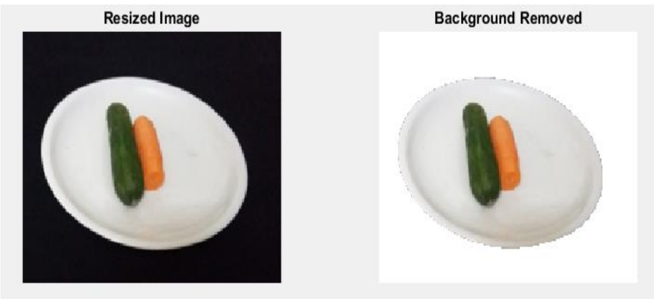

Figure 3.
Removal process of the image background.

After the background removal process, the boundary of the segmentation area of interest was identified to achieve proper contour initialization, which will enhance the segmentation results of the snake method.

In this step, the image is changed to "*hsv*" channels, and the channel with the clearest contrast between the object and the shadow is selected. The results are shown in Figure 4 where the area of the food on the plate was detected after the background removal process. Thereafter, the initial contour can be placed around the area of interest where the food boundary is identified.

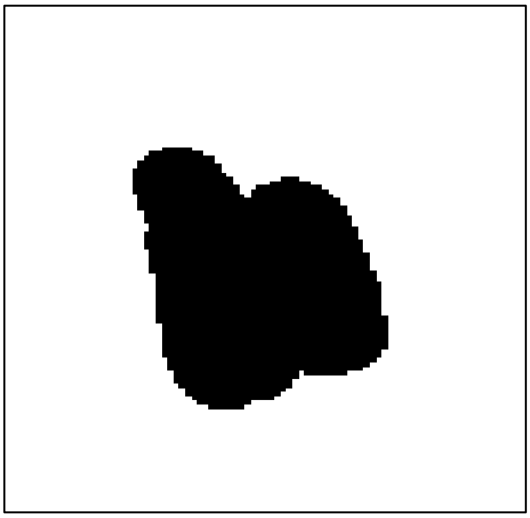

Figure 4.
Image of the area of interest detection.

The final step in the image preprocessing stage is to smooth the images using a Gaussian filter after the background removal process, prior to the application of the active contour method. Figure 5 illustrates the smoothed image and the initial contour, as well as a sample of the snake results after applying it with the optimized energy parameters.

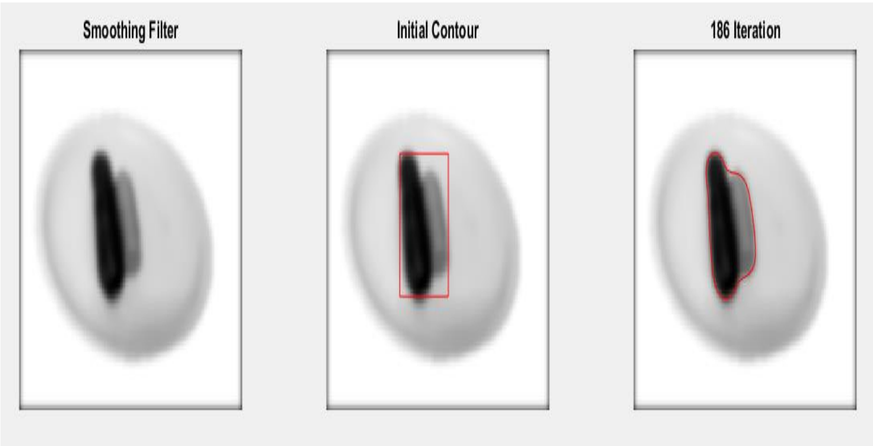

Figure 5.
Smoothened image with the initial contour and the final snake result.

6. Evaluation Parameters

Different evaluation parameters were used in this research; the first two were precision and recall, which are based on region boundaries and are utilized to evaluate the segmentation consistency. The precision and recall parameters were also used in He, et al. [37] for the performance evaluation of their segmentation methods.

Precision is defined as the proportion of boundary pixels in the proposed segmentation method that correspond to the boundary pixels in the ground-truth segmentation. In contrast, recall is defined as the proportion of boundary pixels in the ground truth that are successfully obtained using the proposed segmentation method. However, the precision parameter is sensitive to oversegmentation, whereas the recall parameter is sensitive to undersegmentation. These parameters are calculated using the following equations:

$$\text{Precision} = \frac{\text{Matched } (S_{\text{proposed}}, S_{\text{ground-truth}})}{|S_{\text{proposed}}|}, \tag{12}$$

$$\text{Recall} = \frac{\text{Matched } (S_{\text{ground-truth}}, S_{\text{proposed}})}{|S_{\text{ground-truth}}|}, \tag{13}$$

where $|S_{\text{proposed}}|$ is the total number of boundary pixels detected by the proposed segmentation method, which is our modified active contour in the food image, and is the total number of boundary pixels in the ground-truth image. In this research, ground-truth segmentation was implemented using the same simple object boundary detection method that was also used for contour initialization purposes. We also used a threshold of 1 for our matching method. This indicates that, for every two boundary pixels to be matched, their spatial location distance should not be more than one pixel only.

For an in-depth investigation of the optimized active contour using the ABC algorithm, we applied two additional evaluation parameters, namely, SI and TC. These parameters have been used by other researchers [38] in image segmentation, the purpose is to evaluate segment quality. SI and TC are employed to assess the segmentation quality of the methods used. The formulas for SI and TC are expressed as follows:

$$\mathrm{SI} = \frac{2 * n\{A_1 \cap A_2\}}{n\{A_1\} + n\{A_2\}}, \quad (14)$$

$$\mathrm{TC} = \frac{n\{A_1 \cap A_2\}}{n\{A_1 \cup A_2\}}, \quad (15)$$

where A_1 represents the pixels of the ground-truth segmented area; A_2 denotes the pixels of the segmented area by the modified active contour; and $n\{A_1 \cap A_2\}$ is the number of common pixels between the two areas, which is the number of the correctly segmented pixels in the ground-truth image. In addition, $n\{A_1 \cup A_2\}$ denotes the number of pixels either in A_1 or in A_2 and $n\{A_1\}$ and $n\{A_2\}$ are the number of pixels in the segmented area of the ground truth and by the active contour, respectively. The value of both SI and TC is between 0 and 1. The closer the value is to 1, the higher the quality is of the segmentation result.

Moreover, detection of the ground-truth images was implemented using an automated process based on the information gathered from the "area of interest detection" method discussed in Section 4. However, this proposed process generated several misdetections for some of the food images as shown in Figure 6; the detection method exhibited some noticeable difficulties in detecting foods with a low color density. These coincidences are regarded as one of the drawbacks in areas of interest of the detection method.

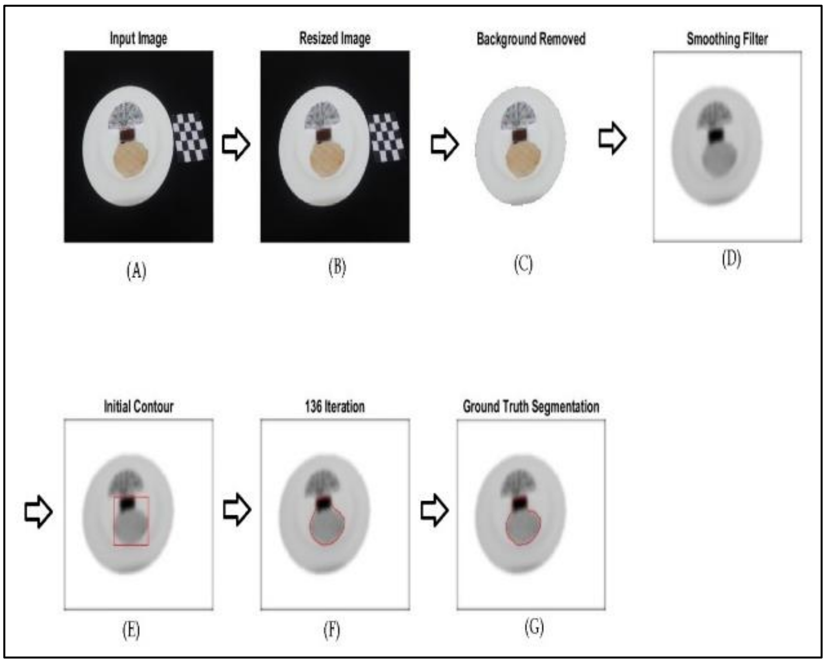

Figure 6.
Food image preprocessing and ground-truth detection methods.

Figure 6 shows the preprocessing methods applied to the input image (A) and the ground-truth detection method, which was also utilized on the image in (D) after the smoothing filter process. The resulting ground-truth detection can be observed in image (G), where the detection method cannot detect the area of the "cheese triangles" in the image because these objects have a lower color density than that of the other food objects in the image. Thus, ground-truth detection encounters a number of difficulties with images that contain foods with a low color density.

7. Experimental Results and Discussion

This section presents the experiments conducted on 102 collected images. In the initial phase, the preprocessing steps outlined in Section 4 are applied to each image before segmentation, using either the original Active Contour (AC) or the modified Active Contour with the ABC algorithm (AC+ABC). After preprocessing, the active contour with its initialized contour is activated to segment the food objects on the plate. A stopping method was introduced to the active contour technique, where the snake movement halts after a certain number of unimproved movements. Additionally, the contour movement stops after a specified number of iterations in the original active contour method, based on the parameter initialization step. Conversely, in the proposed method, the stopping criteria are modified according to the following formula.

$$A_{\mathrm{Difference}} = \frac{|area^{t+1} - area^{t}|}{area^{t+1}}, \quad (16)$$

where $A_{\text{Difference}}$ is the difference value between the last two calculated contour areas and t is the snake iteration number. If $A_{\text{Difference}} \leq 0.00001$, then the snake movement or iteration will stop before the maximum number of iterations is reached. This method prevents the active contour method from consuming unnecessary time without any significant improvement.

Figure 7 presents two samples (a and b) of the same food image, where a is segmented using the original active contour method and b is divided using the modified active contour method with the ABC algorithm. Table 1 presents the differences in the evaluation parameters of some of the segmented images obtained using the original active contour and modified active contour methods. Figure 8 illustrates the segmentation process on seven images from the 102 food images that we captured. As shown in the figure, the segmentation results of the proposed AC+ABC method demonstrate significant improvement compared with the original AC method. Moreover, most of the segmentation performed using the proposed AC+ABC method was achieved with fewer iterations than with the original AC method. This indicates that the optimization process using the ABC algorithm improved the segmentation performance of the original active contour concerning both segmentation quality and speed.

Table 1 presents the four segmentation evaluation parameters selected for this study. The performance of the modified AC+ABC method demonstrates a significant improvement compared to the original AC method. The evaluation metrics precision, recall, SI, and TC indicate that the segmentation quality of the AC+ABC method outperforms the original AC method. Most results exceeded those of the original AC by more than 50%. This suggests that optimizing the external energy equation of the active contour using the ABC algorithm had a notable impact on the segmentation performance of the active contour method.

Table 1.
Values of the four segmentation evaluation parameters for the selected food images.

	Basic AC				Modified AC+ABC algorithm			
Image no.	**Precision**	**Recall**	**SI**	**TC**	**Precision**	**Recall**	**SI**	**TC**
1	35.86	19.40	0.39	0.25	62.76	67.16	0.85	0.74
2	2.67	1.26	0.02	0.01	54.67	39.62	0.57	0.40
3	19.75	9.38	0.22	0.13	42.04	46.35	0.56	0.38
4	22.58	11.17	0.33	0.20	39.35	36.70	0.45	0.29
5	2.96	2.81	0.03	0.02	72.59	51.12	0.89	0.81
6	36.17	17.54	0.38	0.23	60.28	43.13	0.71	0.55
7	9.60	13.95	0.12	0.07	52.00	70.93	0.75	0.60

8. Conclusion

In this research, the active contour (snake) image segmentation method was modified using the ABC algorithm to optimize the parameters of the external energy equation employed by the original active contour method. The modified AC method was applied to 102 collected food images to segment the food objects in the images. The results showed that the influence of the optimized parameters improved the segmentation performance of the original active contour concerning the segmentation quality and convergence speed. Most of the segmentation process results achieved outstanding performance. However, some preprocessing methods utilized in this study negatively affected food image segmentation (ground-truth detection method). Moreover, an in-depth investigation of food image segmentation of connected food images is necessary using the modified active contour.

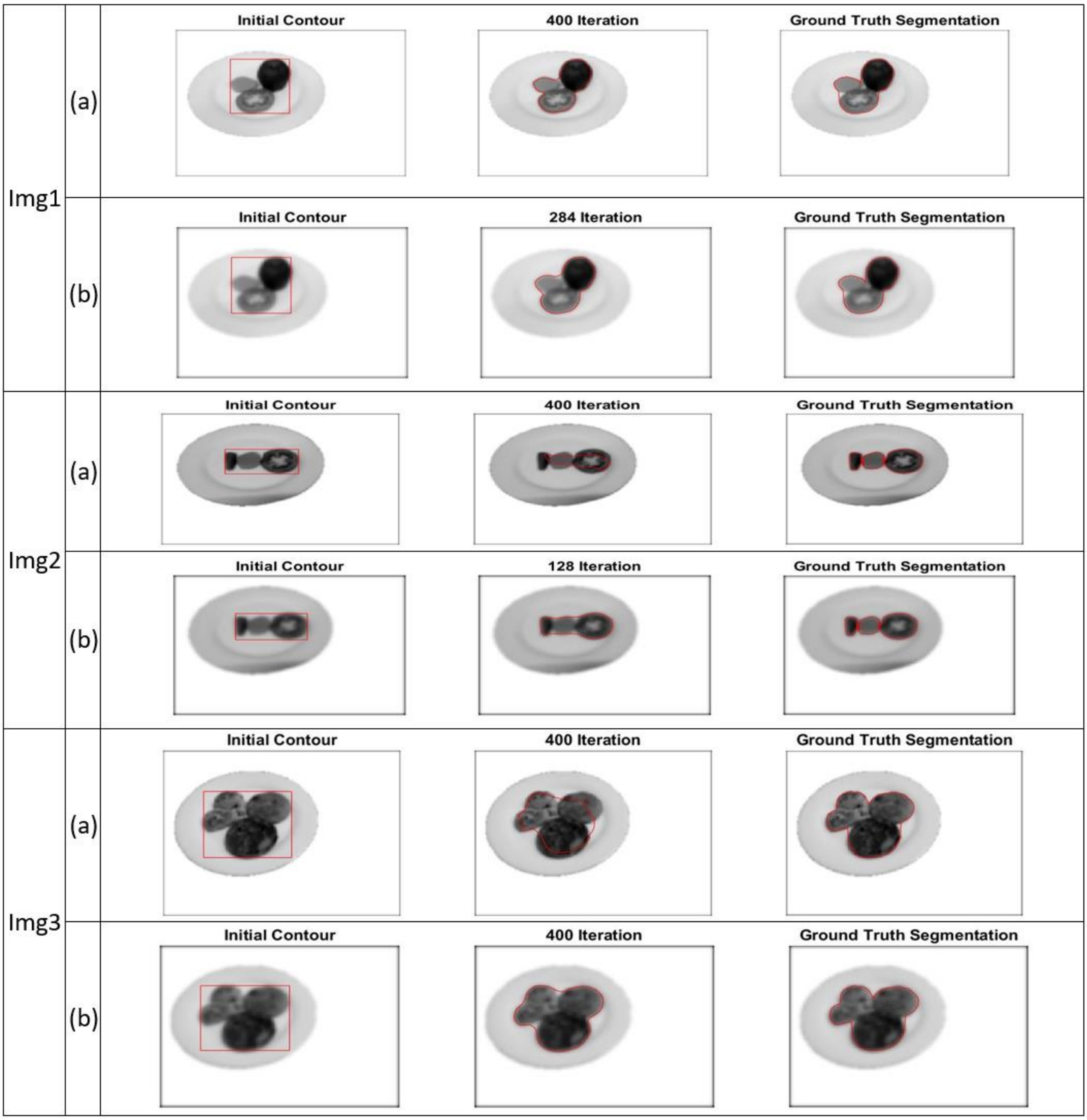

Figure 7.
(Image 1-3): Food image segmentation for seven selected images using the basic AC (a) and modified AC+ABC (b) methods.

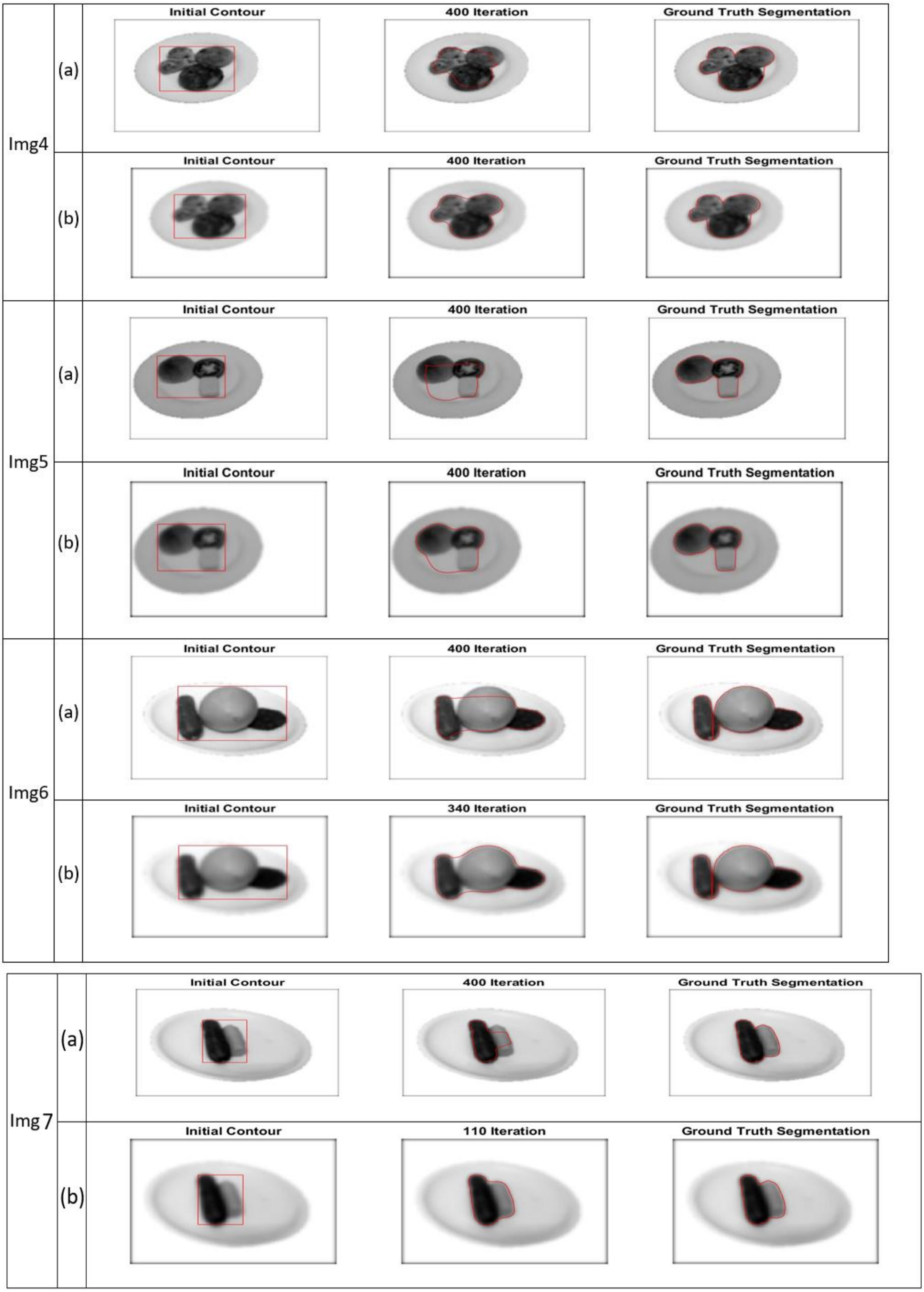

Figure 8.
(Image 4-7): Food image segmentation for seven selected images using the basic AC (a) and modified AC+ABC (b) methods.

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