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CT Liver Segmentation using Artificial Bee Colony Optimisation

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Abstract

The automated segmentation of the liver area is an essential phase in liver diagnosis from medical images. In this paper, we propose an artificial bee colony (ABC) optimisation algorithm that is used as a clustering technique to segment the liver in CT images. In our algorithm, ABC calculates the centroids of clusters in the image together with the region corresponding to each cluster. Using mathematical morphological operations, we then remove small and thin regions, which may represents flesh regions around the liver area, sharp edges of organs or small lesions inside the liver. The extracted regions are integrated to give an initial estimate of the liver area. In a final step, this is further enhanced using a region growing approach. In our experiments, we employed a set of 38 images, taken in pre-contrast phase, and the similarity index calculated to judge the performance of our proposed approach. This experimental evaluation confirmed our approach to afford a very good segmentation accuracy of 93.73% on the test dataset.

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Keywords: Medical imaging, image segmentation, artificial bee colony optimisation, region growing

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1. Introduction

Accurate liver segmentation is a crucial task in computer-aided diagnosis (CAD) systems. A CAD system typically comprises the following main phases: pre-processing, segmentation and classification. Pre-processing is often employed to remove image noise, enhance image quality, and facilitate the distinction of the different organs or regions of interest. A common approach for this is through the use of image filters and image transformations. In our proposed approach, we perform contrast stretching to emphasis the ribs in the image, facilitate connecting the ribs and separating the liver from adjacent flesh and muscles areas.

The main challenge is clearly that of liver segmentation and is consequently also the main focus of our paper. The difficulty here arises from the similarity of the intensity values of the liver area to other adjacent organs such as stomach, kidney and spleen. In this paper, we present a liver segmentation algorithm based on artifical bee colony optimisation. In particular, we employ an artifical bee colony (ABC) algorithm to cluster the different intensity values and hence regions in abdominal CT images. Each cluster is then separated and manipulated using morphological

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operations. The clusters are integrated to obtain the segmented liver region which is futher enhanced using a region growing technique to yield the final segmentation. Experimental evaluation is performed on a dataset of 38 images, taken in pre-contrast phase, and the similarity index calculated to judge the performance of our proposed approach.

The remainder of the paper is organised as follows. Section 2 gives an overview of the artifical bee colony algorithm. Section 3 provides a brief description of region-growing image segmentation. Details of our proposed approach are given in Section 4. Section 5 presents our experimental evaluation, while Section 6 concludes the paper.

2. Artificial bee colony optimisation

The artificial bee colony (ABC) algorithm is a swarm intelligence algorithm based on the foraging behaviour of honey bee colonies[4,1]. Here, an artificial bee colony comprises three groups: employed bees, onlookers and scouts. Employed artificial bees represent the first half of the colony, while the second half includes the onlookers. For each food source there is one employed bee. In ABC, the population consists of food sources, where each food source represents a possible solution to the problem at hand. Each solution is associated with a nectar amount of the food source which represents the fitness value of the solution.

ABC proceeds in the following steps, which are also summarised in Algorithm 1.

- **Step 1:** The ABC generates a randomly distributed initial population of N_S solutions (food source positions). Each solution x_i ($i = 1, 2, \ldots, N_S$) is a D-dimensional vector.

- **Step 2:** Each solution in the population is evaluated by calculating its fitness function, and the best solution in the population is stored.

- **Step 3:** The cycle counter is initialised, and the following steps are repeated until a defined termination criterion (e.g., maximum number of cycles) is met.

- **Step 4:** A new solution is generated from each old solution as

  $$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}), \phi_{ij} \in [-1, 1], \tag{1}$$

  where $k \in \{1, 2, \ldots, NS\}$, $j \in \{1, 2, \ldots, D\}$ and $i \neq k$.

- **Step 5:** Each solution in the population is evaluated by calculating its fitness function, and the best solution in the population is stored and assigned as

  $$f(x_i) = \begin{cases} \frac{1}{1+f(x_i)} & \text{if } f(x_i) \geq 0 \\ 1 + abs(f(x_i)) & \text{if } f(x_i) < 0 \end{cases}$$

- **Step 6:** The probability of each solution is calculated in order to generate a new trail solution v_i by an onlooker bee. The associated probability of each food source P_i is defined as

  $$P_i = \frac{f_i}{\sum_{j=1}^{NS} f_j}. \tag{2}$$

- **Step 7:** The trail solution is generated and evaluated. If it is better than or equal to the old solution, then the old solution is replaced with the new solution, otherwise the old solution is kept. The best solution is stored. If the food source cannot be improved for a set number of cycles, it is abandoned and replaced with a new food source by a scout.

Algorithm 1 ABC algorithm

```
Generate the initial population $x_i$ randomly, $i = \{1, \ldots, NS\}$ {**initialisation**}
Evaluate fitness function $f(x_i)$ of all solutions in the population
Keep the best solution $x_{best}$ {**memorise best solution**}
Set cycle=1
**repeat**
    Generate a new solution $v_i$ from $x_i$ as $v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj})$, $\phi_{ij} \in [-1, 1]$, $k \in \{1, 2, \ldots, NS\}$, $j \in \{1, 2, \ldots, D\}$
    and $i \neq k$ {**employed bees**}
    Evaluate fitness function $f(v_{ij})$ for all solutions in the population
    Keep the best solution between current and candidate solutions {**greedy selection**}
    Calculate probability $P_i$ for $x_i$, where $P_i = \frac{f_i}{\sum_{j=1}^{NS} f_j}$
    Generate new solutions $v_i$ from the selected solutions depending on $P_i$ {**onlooker bees**}
    Evaluate fitness function $f_i$ for all solutions in the population
    Keep the best solution between current and candidate solutions {**greedy selection**}
    Determine abandoned solutions and replace with new random solutions $x_i$ {**scout bee**}
    Keep the best solution $x_{best}$ found so far in the population
    cycle = cycle + 1
**until** cycle $\leq MCN$
```

3. Region growing segmentation

Segmentation methods can be grouped into edge-based and region-based approaches. In edge-based segmentation, edges of objects are determined and from these object regions inferred. A common challenge here is that edge contours are often not closed curves, making identification of regions difficult. In contrast, region-based segmentation applies the concept of similarity between neighbouring pixels. The best known region-based segmentation methods are region growing, region split and merge[3], watershed[6] and level set algorithms[2].

Region growing segmentation starts with seed points and then evaluates similarity of neighbouring pixels and proceeds as laid out in Algorithm 2. Advantages of region growing as a segmentation technique include relatively low computational cost and simplicity, while since being based on the seed points, it can also eliminate user interaction. For similarity, different criteria such as pixel intensity, grayscale texture or colour can be employed[8].

Algorithm 2 Region growing algorithm

```
Obtain starting seed points and label them.
Add all pixels to a queue.
Proceed with neighbouring pixels and check their connectivity, using a chosen similarity measure.
Add each pixel to the relevant labelled region.
Extract the binary image of the labelled regions of the seed points.
Multiply the original image by the binary image to obtain the segmented region.
```

4. Proposed CT liver segmentation approach

Our proposed segmentation approach consists of three main phases:

- **Pre-processing phase:** Pre-processing is relatively simple, and designed to filter out patient information and connecting ribs[7].
- **Artificial bee colony phase:** This is the most important phase and performs the initial segmentation. This is done by clustering the image into a number of regions using artificial bee colony optimisation, followed by morphological processing[5].

- **Region growing phase:** In the final phase, the image segmentation is enhanced by using a region growing technique. The segmented image is then validated using the similarity index meaure to calculate segmentation accuracy.

Figure 1 shows the architecture of the proposed approach for liver image segmentation. In the following, we describe each phase in detail, along with the steps involved and the characteristics of each phase.

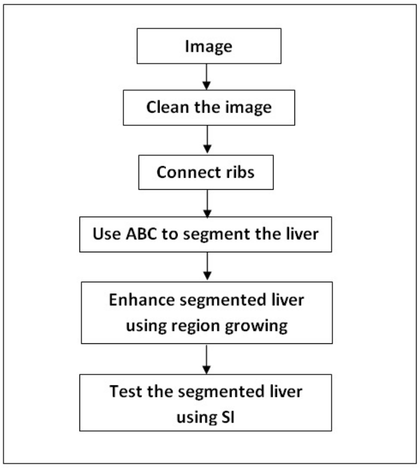
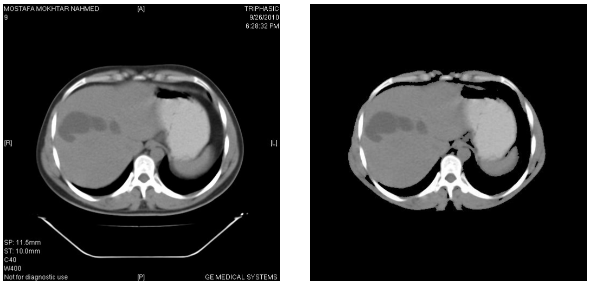


Fig. 1. Overview of proposed liver segmentation approach.

4.1. Pre-processing phase

In the pre-processing stage, which follows our earlier work in[9], we employ a median filter to clean/remove the image annotation and perform contrast stretching for connecting the ribs.

Image cleaning removes the patient information and machine's bed from the image to facilitate the subsequent operations. Figure 2 shows an example of an image before and after cleaning.



(a) (b)

Fig. 2. Cleaning image: (a) original image, (b) cleaned image.

The employed ribs boundary algorithm then overcomes the problem of flesh and muscles areas which are adjacent and connected to the liver. It uses contrast stretching and a threshold (close to white) to isolate the ribs. In the original image, it draws a line between the edges of the ribs to connect them and separate the muscles from the liver tissues. Figure 3 gives an example of the obtained results.

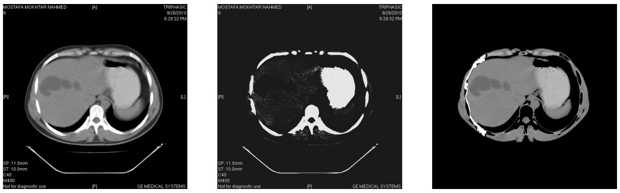

(a) (b) (c)

Fig. 3. Connecting ribs in the image: (a) original image, (b) after contrast stretching filter, (c) connected ribs.

4.2. *Artificial bee colony phase*

Our artificial bee colony algorithm effectively creates a multi-agent system modelling a colony of artificial bees to solve an optimisation problem. In our proposed approach, we use ABC as a clustering technique for CT images in order to accurately segment the liver. The parameter settings of the ABC algorithm need to be carefully considered. In particular, the number of clusters is important in this process. We have two extreme intensity values corresponding to the (black) background and the (white) bones. Besides that, we have liver boundaries, lesions and other organs. We experimentally confirmed six clusters to lead to good segmentation results; other parameter settings are specified in Table 1.

Table 1. Parameters of proposed approach

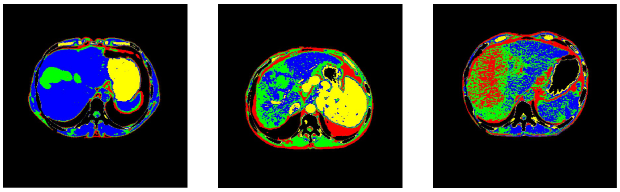
Parameter	Setting
Initial population	50
Food	25
Solutions	50
Maximum cycle number	30
Clusters	6

A fitness function is required to determine the new solution in every iteration. The resulting solution of clusters (global parameters or best solution) will be the centroids of the required clusters. Algorithm 3 details our procedure of using ABC as a clustering technique to segment the liver.

Algorithm 3 ABC for liver segmentation

```
Determine the number of clusters, number of colony and iterations for starting ABC algorithm.
Pass the CT image to ABC.
Extract the global parameters, which represent the centroids of the clusters.
Sort the cluster centroids.
Extract the binary clustered images.
Change the values of a part of right bottom quarter of the image to black. This cuts the closed organ of spleen, and prevents the stomach and spleen from being filled in the next step.
Fill the holes for every clustered image and remove small objects.
Exclude the lowest and highest clusters and combine the clustered images.
Multiply the resulting binary image by the original image to get the segmented image.
```

Figure 4 shows a number of examples of clustered images using our ABC algorithm.

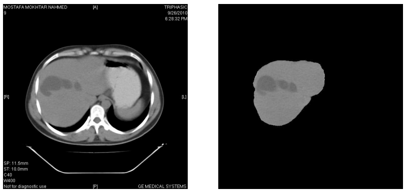


(a) (b) (c)

Fig. 4. Clustered results of different images using ABC.

4.3. Region growing phase

As mentioned, the advantages of region growing are simplicity and low computational complexity. In our approach, we employ region growing to further enhance the initial segmentation obtained from the ABC phase. The ABC segmented image is enhanced using region growing. Figure 5 shows an example result of the region growing phase.



(a) (b)

Fig. 5. Liver segmentation using region growing: (a) original image, (b) region growing image.

5. Experimental results

For evaluation, we employed a set of 38 CT images taken in the first phase of CT scan before the injection with contrast material.

Figure 6 gives an example of the extracted binary images corresponding to the different clusters obtained from our ABC algorithm.

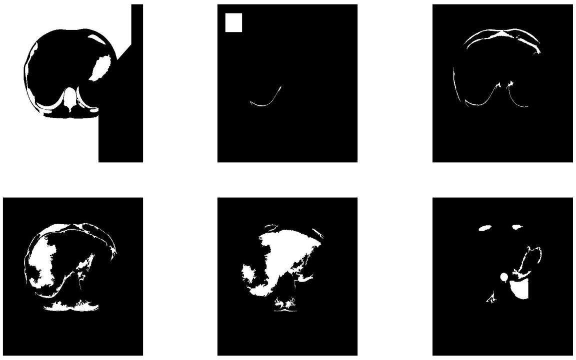


Fig. 6. Cluster binary images resulting from ABC clustering.

Figure 7 shows the resulting binary image of ABC and the liver segmented image.

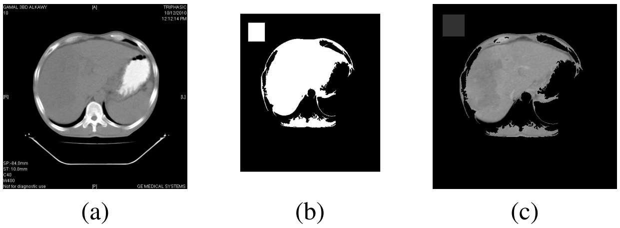


Fig. 7. ABC liver segmentation: (a) original image (b) ABC binary image, (c) ABC segmented image.

Finally, the segmented image is enhanced using region growing. Figure 8 shows the difference between the segmented image and the annotated one. As we can see, it shows a very thin boundary of the liver as difference.

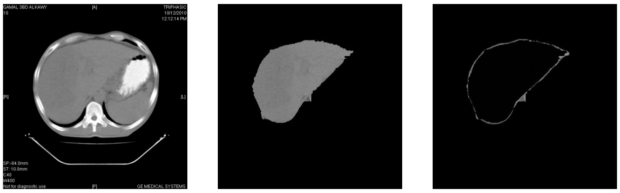


Fig. 8. Final liver segmented image compared to the annotated image: (a) original image, (b) segmented image, (c) difference image

Quantitative evaluation is performed using the similarity index (SI) which is defined as

$$SI(I_{auto}, I_{man}) = \frac{I_{auto} \bigcap I_{man}}{I_{auto} \bigcup I_{man}} \tag{3}$$

where I_{auto} is the binary automated segmented image, resulting from the phase of final segmentation of the whole liver in the used approach and I_{man} is the binary manually segmented image (by a radiology specialist).

Table 2 gives the results of our proposed approach compared to a region growing segmentation approach. As we can see from there, the average performance of liver image segmentation is drastically improved using our proposed segmentation algorithm. Segmentation using region growing yields an average SI of 84.82%. In contrast, our proposed approach gives an average SI of 93.73%.

Table 2. Segmentation results of proposed approach compared and region growing.

image	region growing	proposed algorithm
1	0.881	0.981
2	0.927	0.911
3	0.831	0.947
4	0.740	0.910
5	0.868	0.969
6	0.849	0.951
7	0.956	0.949
8	0.934	0.891
9	0.923	0.951
10	0.939	0.945
11	0.890	0.953
12	0.893	0.935
13	0.757	0.940
14	0.917	0.959
15	0.902	0.935
16	0.938	0.948
17	0.910	0.940
18	0.898	0.905
19	0.536	0.917
20	0.880	0.925
21	0.708	0.924
22	0.616	0.945
23	0.696	0.945
24	0.820	0.913
25	0.913	0.902
26	0.930	0.940
27	0.921	0.951
28	0.908	0.948
29	0.920	0.948
30	0.947	0.945
31	0.941	0.921
32	0.942	0.921
33	0.888	0.905
34	0.856	0.938
35	0.855	0.961
36	0.913	0.942
37	0.671	0.959
38	0.661	0.946
average	0.848	0.937

Table 3 provides a further comparison of our results compared to other segmentation methods.

Table 3. Comparison of proposed approach with other methods.

method	average SI
Region growing	84.82
Level set	92.10
k-means with RG	92.38
proposed approach	93.73

6. Conclusions

Liver segmentation is an important process for computer-aided diagnosis. In this paper, we have presented a liver segmentation algorithm based on a clustering process that is optimised by an artifcial bee colony algorithm. Following a pre-processing stage that is designed to remove image annotations and connect the ribs, ABC is employed to obtain an initial segmentation of the liver area. This is then refined by a region growing approach to arrive at the final segmentation. Experimental results on a challenging dataset of 38 CT images shows our approach to give very good segmentation performance and to outperform several other segmentation algorithms.

References

1. B. Basturk, D.Karaboga, An Artificial Bee Colony (ABC) Algorithm for Numeric function Optimization, IEEE Swarm Intelligence Symposium 2006.
2. V. Caselles, R. Kimmel, and G. Sapiro. ”Geodesic active contours”, Int J Comput Vis, vol 22, pp. 61-79, 1997.
3. R. C. Gonzales, R. E. Woods, ”Image segmentation”, in *Digital Image Processing*, 3^{rd} ed., Prentice Hall, 2008.
4. D. Karaboga, An Idea Based On Honey Bee Swarm For Numerical Optimization, Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005.
5. M. Kowalczyk, P. Koza, P. Kupidura, J. Marciniak, ”Application of mathematical morphology operations for simplification and improvement of correlation of image in close-range photomography”, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B5, 2008
6. F. Meyer , ”Topographic distance and watershed lines”, Signal Processing, Vol. 38, 1993, pp. 113-125.
7. A. Mostafa, H. Hefny, N. I. Ghali, A. Hassanien and G. Schaefer, ”Evaluating the Effects of Image Filters in CT Liver CAD System”, IEEE-EMBS International Conference on Biomedical and Health Informatics, 2012.
8. O. E. Ramos, and B. Rezaei, Scene Segmentation and Interpretation of Image Segmentation using Region Growing. Diss. MSc, Thesis, Computer Vision and Robotics, Universitat de Girona, 2010.
9. A. Zidan, N. I. Ghali, A. Hassanien, H. Hefny, ”Level Set-based CT Liver Computer Aided Diagnosis System”, International Journal of Imaging and Robotics, Vol. 9, 2013.