# Moth-flame Optimization Based Segmentation for MRI Liver Images

**Conference Paper** · January 2018

DOI: 10.1007/978-3-319-64861-3_30



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# Moth-flame Optimization based Segmentation For MRI Liver Images

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**Abstract.** One of the most important aims in computerized medical image processing is to find out the anatomical structure of the required organ. The hepatic segmentation is very important for surgery planning and diagnosis. The difficulty of segmentation rises from the different volumes, the different lobes and the vascular arteries of liver. This paper proposes a successful approach for liver segmentation. The proposed approach depends on Moth-flame optimization (MFO) algorithm for clustering the abdominal image. The user picks up the required clusters that represent the liver to get the initial segmented image. Then the morphological operations produce the final segmented liver. A set of 70 MRI images, was used to segment the liver and test the proposed approach. Structural Similarity index (SSI) validates the success of the approach. The experimental results showed that the overall accuracy of the proposed approach, results in 95.66% accuracy.
**Keywords**: Mouth-flame optimization, clustering, segmentation.

## 1 Introduction

Computerized medical imaging analysis aims to detect and delineate anatomical structures. It has gained significant importance in hepatic procedures, specially in oncology to detect tumors and lesions, quantify the ratio of tumorss volume and liver's volume (future liver remnant volume and total liver volume). Also, in the context of liver transplantation, graft from living donors is performed due to the unavailability of donors. This surgical procedure need to determine the donor's liver volume.

The automated diagnosis systems that use medical imaging, can be handled using bio-inspired algorithms. These algorithms raised out of the careful observation of nature. They try to mimic the behaviour of animals, insects and birds. The individual behaviour of the swarm is simple, but the coordination between the individuals creates an amazing structured social organization.

The used Mouth-flame algorithm is one of the bio-inspired algorithms. It depends on simulating the behaviour of the Mouth-flame in navigating using the light.

Velayudham A. et al. [2] proposed a framework for de-noising, detecting and classification of the tumor in CT medical images. Initially unwanted noise is removed by using Dual Tree Complex Wavelet Packets and Empirical Mode Decomposition. Then tumors are segmented using K-means clustering technique. Finally, in classification phase, a Cuckoo-Neuro Fuzzy algorithm is improved for detection of the tumor region. The method gives 96.3%accuracy.

Sankari L. [6] presented an efficient hybrid technique for image segmentation. This hybrid algorithm contains two segmentation processes; the Glowworm swarm optimization (GSO) and the Expectation-Maximization (EM) based on clustering methods. The proposed approach is compared with standard (Gaussian mixture models) GMM-EM by using a Berkleys image data set. Rand index measure and GCE (Global consistency Error) are using for measuring The performance.

Parag P. et al. [5] presented a method for colour classification and image segmentation, based on a fuzzy system. The used algorithm is Comprehensive Learning Particle Swarm Optimization(CLPSO) that tried to overcome the drawback of original Particle Swarm Optimization (PSO). The proposed aims to maximize a fitness criterion and small number of rules. At the end, the highest fitness value is chosen as the best set of fuzzy rules for image segmentation.

Xiang L. et al. [8] have developed a method for automatic diagnosis of cirrhosis with ultrasound images. They evaluated their method on a dataset consisting of 91 ultrasound images, in which 44 images are from normal people and 47 images are from people with cirrhosis. First liver capsule is detected by using two stages, sliding window detection and dynamic programming based linking, then convolutional neural network (CNN) model is used to separate features from the image patches cropped around the liver capsules. Finally, a trained support vector machine (SVM) classifier is utilized to classify the sample into normal or infected cases.

Amitha R. et al. [1] proposed an automated approach for segmenting and detecting liver and tumor from CT images. Robustness to noise is achieved by embedding MRF (Markov Random Field) to traditional level set energy function. Any ambiguity in segmentation is processed by shape analysis. SFM (Sparse field Method) is used to reduce the time of implementation. Then, tumours are classified into cancerous or benign using SVM (Support Vector Machine) classifier.

Vincey J. et al. [3] presented a framework for a Computer Aided Diagnosis System. It is implemented on the abdominal CT images to detect the liver tumor. This method includes 5 stages: first phase is image acquisition for liver. In the second Phase: the region growing technique is used to segment liver. Third phase is noise removal by using a Gaussian filter. Fourth phase is feature extraction. Finally , classification algorithm is achieved by Hidden Markov Model(HMM) that reduces the time consumed.

The remainder of this paper is ordered as follows. **Section (2)** gives an overview about MFO algorithm. **Section (3)** is dedicated to the description of the proposed approach for liver segmentation. **Section (4)** shows the experimental results of the proposed approach. Finally, conclusions and future work are discussed in **Section (5)**.

## 2 Moth-flame optimization algorithm

The MFO is one of the recent swarm optimization techniques. It is inspired by the navigation method of moths in the night called transverse orientation. Moths and flames actually are the main components in the MFO where they differ in the way of dealing and updating during each iteration. In this algorithm, it is supposed that the moths are the candidate solutions and the moths' positions are the problem's variables. Moths can fly in I-D, 2-D, 3-D, or hyper dimension space with changing their position vectors. Moths are the search agents that move around the search area; however flames are the optimum position of moths. Each moth is moving and searching around a flame. It updates its position to a new one when it finds a solution better than the current one. The main updating mechanism of moths is the logarithmic spiral.

### 2.1 Inspiration

Moths are insects, highly similar to the butterflies. There are two main stages in their lifetime: larvae and adult. The larvae is converted to moth in cocoons. The most interesting fact about moths is their special navigation method at night. They have been evolved to fly at night using the moon light. They utilize a mechanism called transverse orientation for navigation. A moth follows the moon by flying using a fixed angle with respect to it to travel in a straight path for long distances. But the moth flies spirally around the lights when it is very close. They are tricked by the lights and use the same fixed angle. This transverse orientation seems useful only when the light is very far. When the light is too close, it directs the spiral path towards the light [4].

### 2.2 Mathematical Formulation

According to the behaviour of converging towards an artificial light, the steps of the MFO are listed as follows.
**Step 1: Position Matrix initialization**
MFO algorithm can be modelled by the position of moths and flames. Each moth and flame can be in different dimensions in space by setting a number of variables for each moth and flame. It is represented in two types of matrices. The first represents the position matrix of moths, and the second represents the position matrix of flames.

$$M = \begin{pmatrix} M_{1,1} \ M_{1,2} ... \ M_{1,d} \\ M_{2,1} \ M_{2,2} ... \ M_{2,d} \\ M_{n,1} \ M_{n,2} ... \ M_{n,d} \end{pmatrix} F = \begin{pmatrix} F_{1,1} \ F_{1,2} ... \ F_{1,d} \\ F_{2,1} \ F_{2,2} ... \ F_{2,d} \\ F_{n,1} \ F_{n,2} ... \ F_{n,d} \end{pmatrix}$$

Where M is the position matrix of moths, F is the position matrix of flames, n is the number of moths and d is the number of variables (dimensions).

**Step 2: values of fitness function**

To evaluate each moth, a fitness function that can generate fitness values by inputting the position of moths would be given during optimization, and the matrix Om is employed to store the corresponding fitness values of moths.

$$om = \begin{pmatrix} om_1 \\ om_2 \\ om_n \end{pmatrix}$$

The matrix OF is employed to store the corresponding fitness values of flames.

$$OF = \begin{pmatrix} OF_1 \\ OF_2 \\ OF_n \end{pmatrix}$$

**Step 3: initialization of iteration**

The general texture of MFO algorithm contains three-tuple of approximation function which is characterized as:

$$MFO = (P, I, T) \tag{1}$$

where P is a function which randomly creates the population of moths and their fitness values, OM is the fitness function(M), I is the essential function that defines how the moths move around the search area.

The initialization of M and F can be calculated as follows.

$$M(a,b) or f(a,b) = (ub(a) - lb(a)) * rand + lb(a) \tag{2}$$

Where ub and lb represent upper and lower limits of variables, rand is the random number generated with uniform distribution in the interval [0, 1], a denotes the number of moths or flames and b denotes number of variables or dimensions.

After the initialization, the I function runs repeatedly till the T termination criterion is met. In I function, the position of each moth is updated with regard to corresponding flame using the logarithmic spiral function as follows.

$$Mi = S(Mi, fj) \tag{3}$$

where S is the spiral function, $M_i$ refer to $i^{th}$ moth, $F_j$ indicates $j^{th}$ flame.

The logarithmic spiral is given by the following equation:

$$S(M_i, f_j) = Di.e^b t.cos(2t) + F_j \tag{4}$$

Where $D_j$ refers to the distance among the $i^{th}$ moth and $j^{th}$ flame and is computed as:

$$D_i = F_j M_i \tag{5}$$

where b is a constant for defining the spiral function and t is a random number in [1, 1].

**Step 4 : selection of optimum flames**: The Update of flame's position happens if any of the moths becomes fitter than the flame. According to this rule, when the iteration criterion is met, the better solution would be returned as the best gained approximation

## 3 Moth-flame proposed approach for CT liver segmentation

Moth-flame proposed an approach for CT liver segmentation, consists of some main phases. It starts with a preprocessing phase, followed by MFO algorithm to cluster the image into a number of predefined clusters. A binary statistical image is multiplied by the resulting clustered image to remove a great part of the abdominal image, which includes the stomach and the spleen organs. Then the clusters that represent the liver are chosen by the user to extract the initial segmented liver. Finally, the initial segmented liver is enhanced using the morphological operations. Algorithm (1) describes the procedures of the proposed approach. The following subsections will describe the details of the proposed algorithm as follows.

**Algorithm 1** The proposed liver segmentation approach

1: Sum all manual segmented images in one binary image as a statistical image.
2: Use morphological operations to clean the image from the existing machine's image annotation.
3: Use MFO to segment the image into a number of clusters according to the intensity values.
4: Multiply the prepared binary statistical image by the MFO clustered image.
5: Pick up the required clusters manually to separate these clusters in a binary image and multiply it by the original image to get the initial segmented liver.
6: Enhance the initial segmented image using the morphological operations.
7: Validate the accuracy of the segmented image using Structural similarity index (SSI).

### 3.1 Preprocessing phase

This phase is compromised of two steps, including the main step of preparing the statistical image. It also includes cleaning the image's annotations to prepare it for MFO clustering step.
**Statistical image:** To prepare the statistical image, all the images of the dataset should be converted into binary format. The white pixel in the binary image will represent an occurrence of liver in an abdominal image. Every image will be summed to one matrix which represents the final statistical image.
**Image Cleaning phase:** Every medical image has some information about the patient and the imaging machine. Cleaning removes the patient's information from the image, utilizing some morphological operations.

### 3.2 Moth-flame Optimization phase (MFO)

The main purpose of using MFO algorithm is to cluster the intensity values of an image. The clustered image helps to segment the initial liver. As all the bio-inspired algorithms, MFO algorithm has to set values to a number of parameters. The main key of MFO algorithm is to set the values of the parameters, which include the search agents number, the iterations number and the number of the predefined clusters. These parameters will be tested before execution to get the best values that proves better performance of the algorithm. The comparison of the fitness values defines the best solution through the iterations of the algorithm. Finally, the best solution will define the required clusters. Then the clusters' values are sorted and labelled. The distance between the intensity value of every pixel and found clusters' values, is calculated and the appropriate cluster's label is assigned to this pixel.

### 3.3 Statistical image and image enhancement phase

Since, the range of intensity values of liver is similar to other organs. The usage of statistical image removes a great part of other organs' tissues. The binary statistical image, which represents the liver statistical occurrence, is multiplied by the image, resulting from MFO. Then, the required clusters are picked up manually and multiplied by the original image to get the initial segmented liver. Finally , the morphological operations are used to fill the holes of the binary image and remove the small objects outside the liver.

## 4 Experimental results and discussion

The experiments of the proposed approach of segmentation using MFO, statistical image and morphological operations will be covered in this section. A set of 70 MRI images were used in the experiments to test the proposed approach.

Parameters in MFO algorithm are the major affecting factor in a successful implementation. Initially, The proposed algorithm is tested using 5 randomly selected MRI images from the used dataset. There are three main parameters affecting the accuracy and speed using MFO algorithm. 1) Search agents size, which represents the total number of moths. 2) Number of iterations used to test MFO algorithm. 3) Number of clusters, which represents the number of classes used to segment the liver. Initially, The proposed algorithm is tested using 5 randomly selected MRI images from the used dataset. Each value for each parameter is tested independently on the five images. Then we get the average results of parameter's value. The affecting parameters are explained as follows.

1. Search agents size:
   It represents the total number of moths, used to get the main clusters centroids. Table (1) shows the results of using different values of search agents to

evaluate its affect on MFO algorithm performance. The first column represents the search agents sizes, ranging between 5 to 50. The next five columns are the image number. Finally, the last column represents the average accuracy result for each search agent size. It is shown in the table that the best result is 96.488% for 30 search agents.

**Table 1.** Parameter setting for search agents size

| Search Agt.s | 1 | 2 | 3 | 4 | 5 | Result |
|---|---|---|---|---|---|---|
| 4 | 0.9647 | 0.9054 | 0.9741 | 0.94 | 0.9439 | 0.94562 |
| 5 | 0.9701 | 0.9508 | 0.9579 | 0.9569 | 0.9692 | 0.96498 |
| 6 | 0.9711 | 0.9521 | 0.9759 | 0.947 | 0.9613 | 0.96148 |
| 7 | 0.9651 | 0.9561 | 0.9747 | 0.945 | 0.9624 | 0.96066 |
| 8 | 0.9705 | 0.9583 | 0.969 | 0.9548 | 0.9634 | 0.9632 |
| 9 | 0.9672 | 0.9574 | 0.9739 | 0.957 | 0.9607 | 0.96324 |
| 10 | 0.9699 | 0.9515 | 0.9671 | 0.9593 | 0.964 | 0.96236 |
| 20 | 0.9664 | 0.9595 | 0.9685 | 0.9571 | 0.9647 | 0.96324 |
| 30 | 0.9709 | 0.9654 | 0.9706 | 0.9536 | 0.9639 | 0.96488 |
| 40 | 0.9544 | 0.9601 | 0.9754 | 0.9311 | 0.9624 | 0.95668 |

2. Number of iterations:
   It is the number of loops, used to test MFO algorithm. Table (2) shows the results of testing different number of iterations used to test 5 random MRI images through MFO algorithm. The first column represents the number of iterations, ranging between 1 to 30. The next five columns are the image number. Finally, the last column represents the average accuracy result for each number of iterations. The best result, shown in the table, is 96.78% for 7 iterations.

**Table 2.** Evaluating the number of iterations

| Iterations | 1 | 2 | 3 | 4 | 5 | Result |
|---|---|---|---|---|---|---|
| 1 | 0.9690 | 0.9472 | 0.9763 | 0.9522 | 0.9699 | 0.9629 |
| 2 | 0.9696 | 0.9595 | 0.9760 | 0.9619 | 0.9687 | 0.9671 |
| 3 | 0.9503 | 0.9588 | 0.9523 | 0.9671 | 0.9687 | 0.9595 |
| 4 | 0.9637 | 0.9528 | 0.9680 | 0.9361 | 0.9699 | 0.9581 |
| 5 | 0.9652 | 0.9658 | 0.9756 | 0.9627 | 0.9627 | 0.9664 |
| 6 | 0.9708 | 0.9296 | 0.9762 | 0.9603 | 0.9524 | 0.9579 |
| 7 | 0.9697 | 0.9659 | 0.9784 | 0.9601 | 0.9650 | 0.9678 |
| 10 | 0.971 | 0.9504 | 0.9676 | 0.9533 | 0.9664 | 0.9617 |
| 20 | 0.9618 | 0.9603 | 0.9679 | 0.9603 | 0.9618 | 0.9624 |
| 30 | 0.9696 | 0.9643 | 0.9709 | 0.9607 | 0.9664 | 0.9664 |

3. Number of clusters:
   It represents the number of used clusters to test the algorithm to segment the liver. Table (3) shows the results of evaluating different clusters' values on the performance of MFO algorithm. The first column represents the clusters values, ranging between 1 to 10. The next five columns are the image number. Finally, the last column represents the average accuracy result for each clusters value. The best result is shown in the table, is 7 clusters.

**Table 3.** Evaluating the change of the number of clusters

| Cluster | 1 | 2 | 3 | 4 | 5 | Result |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0.9172 | 0.9117 | 0.7139 | 0.6742 | 0.9129 | 0.8260 |
| 4 | 0.9453 | 0.9642 | 0.9679 | 0.9390 | 0.9640 | 0.9561 |
| 5 | 0.9707 | 0.9501 | 0.9740 | 0.8990 | 0.9097 | 0.9407 |
| 6 | 0.9633 | 0.9498 | 0.9528 | 0.9598 | 0.9617 | 0.9575 |
| 7 | 0.9701 | 0.9508 | 0.9779 | 0.9569 | 0.9692 | 0.9649 |
| 8 | 0.9709 | 0.9574 | 0.9588 | 0.9523 | 0.9693 | 0.9618 |
| 9 | 0.9696 | 0.9586 | 0.9736 | 0.9603 | 0.9588 | 0.9642 |
| 10 | 0.9696 | 0.9305 | 0.9728 | 0.9239 | 0.9647 | 0.9523 |

Evaluation is performed using structural similarity index measure(SSIM), which is defined using Eq. 6.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c^2)}{(\mu_x^2\mu_y^2 + c_1)(\sigma_x^2\sigma_y^2 + c_2)} \tag{6}$$

where $SSIM$ is the structural similarity index measure, x is the automatic segmented image, y is the manual segmented image, $\mu_x$ is the average of x,$\mu_y$ is the average of y, $\sigma_x$ is the variance of x, $\sigma_y$ is the variance of y, $\sigma_{xy}$ is the covariance of x and y. Besides, $c_1 = (k_1L)^2$, and $c_2 = (k_2L)^2$, where L is the dynamic range of the pixels values, $K_1 = 0.01$ and $K_2 = 0.03$ by default.

The experiments of using the proposed approach showed a good efficiency. It proved a better performance compared with other traditional and bio-inspired segmentation methods. Table (4) shows the results of the proposed approach. It shows that the performance of the proposed approach is 95.66%.

**Table 4.** Results of proposed approach

| Img No. | MFO | Img No. | MFO | Img No. | MFO |
|---|---|---|---|---|---|
| 1 | 0.971 | 25 | 0.9547 | 49 | 0.9472 |
| 2 | 0.9581 | 26 | 0.963 | 50 | 0.9912 |
| 3 | 0.9756 | 27 | 0.9217 | 51 | 0.9225 |
| 4 | 0.9591 | 28 | 0.9297 | 52 | 0.9862 |
| 5 | 0.9737 | 29 | 0.9313 | 53 | 0.9013 |
| 6 | 0.9608 | 30 | 0.9842 | 54 | 0.9585 |
| 7 | 0.9085 | 31 | 0.9215 | 55 | 0.9081 |
| 8 | 0.96549 | 32 | 0.948 | 56 | 0.9501 |
| 9 | 0.954 | 33 | 0.9526 | 57 | 0.9013 |
| 10 | 0.9574 | 34 | 0.9805 | 58 | 0.9494 |
| 11 | 0.9152 | 35 | 0.9626 | 59 | 0.9159 |
| 12 | 0.9899 | 36 | 0.9961 | 60 | 0.9369 |
| 13 | 0.9608 | 37 | 0.9679 | 61 | 0.9756 |
| 14 | 0.9518 | 38 | 0.9971 | 62 | 0.9576 |
| 15 | 0.9203 | 39 | 0.9594 | 63 | 0.9867 |
| 16 | 0.9152 | 40 | 0.9543 | 64 | 0.9548 |
| 17 | 0.9858 | 41 | 0.9207 | 65 | 0.9574 |
| 18 | 0.99 | 42 | 0.9976 | 66 | 0.95874 |
| 19 | 0.9356 | 43 | 0.9788 | 67 | 0.9823 |
| 20 | 0.9772 | 44 | 0.9759 | 68 | 0.959 |
| 21 | 0.9231 | 45 | 0.9282 | 69 | 0.9929 |
| 22 | 0.9755 | 46 | 0.9954 | 70 | 0.9541 |
| 23 | 0.9754 | 47 | 0.9281 | | |
| 24 | 0.9632 | 48 | 0.9988 | | |
| Result | 0.9566 | | | | |

In Table (5), the result of the proposed approach is compared to other traditional and bio-inspired approaches. The proposed approach, compared to these approaches, achieved the best result.

**Table 5.** Comparison between the proposed approach and other approaches

| Ser. | Approach | Result |
|---|---|---|
| 1 | Region growing (RG) | 84.82 |
| 2 | K-means +RG | 92.38 |
| 3 | Level set | 92.10 |
| 4 | Artificial Bee Colony (ABC) | 93.73 |
| 5 | Grey Wolf (GW) | 94.08 |
| 6 | Proposed approach (MFO) | 95.66 |

## 5 Conclusion and Future work

The proposed approach depends on the Moth-flame Optimizer algorithm in segmenting the liver from MRI images. It results in a clustered image, which is multiplied by the statistical image to remove a part of the abdomen that includes other organs. The required clusters representing the liver is picked up manually to get an initial segmented liver. Then the image is enhanced using some morphological operations to remove the small objects outside the liver boundary. The accuracy of the segmented image is tested using structural similarity index (SSIM). The segmentation of liver using the proposed approach has an average accuracy rate of 95.66% using SSIM measure. The future work will concentrate on a better performance using other bio-inspired algorithms.

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