A Comparative Study on Image Segmentation Based on Artificial Bee Colony Optimization and FCM

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Abstract— The goal of image segmentation is to cluster the pixels of an image into several regions. This article describes the method of image segmentation using Artificial Bee Colony Optimization (ABC). This optimization technique is motivated by intelligent behaviour of honey bees and it provides a population based search procedure. In this article Gaussian Mixture Model (GMM) is used and each pixel class is represented by a single Gaussian function and a mix of Gaussian functions is used to segment the gray image by approximating the image histogram. The parameters of this model are estimated by ABC. Intersecting point of the gaussian functions is considered as the threshold point. The optimization technique is compared with the popular Fuzzy C Means (FCM). The proposed algorithm is found efficient over FCM. The experiment has been done over various gray scale images and segmentation of such images is very difficult due to low contrast, noise and other imaging ambiguities. The results are proved by both quantitative and qualitative measures.

Keywords— Image segmentation, Gaussian Mixture Model(GMM), Fuzzy C Means(FCM), Artificial Bee Colony Optimization(ABC), Medical & Satellite image segmentation, Cluster validity index.

I. INTRODUCTION

Image segmentation is the process of partitioning an image into multiple segments that is sets of pixels. Image segmentation is typically used to locate objects within the image. The result of image segmentation is a set of segments that collectively cover the entire image. The pixels of each region are similar with respect to some characteristics or computed property. Adjacent regions are significantly different with respect to some characteristics (colour, intensity, texture).

Image segmentation is useful in various aspects. Such as segmentation of medical images which can be applied to locate tumours and other pathologies, measure of tissue volumes, diagnosis, study of anatomical structure and other useful tasks are object detection, performing recognition tasks, locating objects in satellite images (roads, forests, crops etc). However segmentation of a satellite image is usually difficult.

There are several general-purpose algorithms and techniques that have been developed for image segmentation. The segmented result totally depends on the robustness of the algorithm applied for segmentation. Segmentation algorithms either measures the homogeneity of a region (thresholding) or check for the discontinuity between disjoint regions (ending edges). Since methods based on the homogeneity offer the advantage of a smaller storage space, fast processing speed and easy manipulation so thresholding techniques are considered as the most popular one.

Here Artificial Bee Colony Optimization (ABC [9]) has been applied as the proposed method for image segmentation. It is motivated by the intelligent behaviour of the honey bees. ABC is an optimization tool. It provides a population based search procedure in which individuals called foods and their positions are modified by the artificial bees with time and the bee’s aim is to discover the food sources with high nectar amount and finally the one with the highest nectar amount. In ABC artificial bees fly around a multidimensional search space, some of them (employed bees and onlooker bees) choose food sources depending on their experience and try to adjust their positions and others(Scout bees) fly and choose food sources randomly without using experience. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. Thus ABC combines local search methods carried out by employed and onlooker bees with global search methods managed by scout bees to balance exploration and exploitation process.

ABC algorithm is used to solve the optimization problem of approximating the one dimensional histogram [14] of the image to be segmented with respect to the Gaussian mixture model (GMM [4]). Parameters of GMM are calculated through the ABC algorithm. Each Gaussian function approximating the histogram represents a pixel class and therefore a threshold point for the segmentation scheme.

Experiment shows that ABC algorithm performs very fast convergence, low computational cost, no need to declare initial no of cluster and it can automatically find the stopping condition. To prove all these criteria it has been compared with the Fuzzy C Means (FCM [15]), which is a popular unsupervised clustering algorithm. But it is necessary for the FCM to specify the no of cluster initially and it is also very difficult to cluster high dimension data set with FCM.

Now the proposed work is explained as follows.
II. ARTIFICIAL BEE COLONY (ABC) OPTIMIZATION

A. Gaussian Mixture Model (GMM)

Consider an image with intensity levels in the range of [0, L-1] whose distribution is displayed within a histogram h(k). In order to simplify the distribution, the histogram is normalized just as a probability distribution function yielding:

\[ h(k) = \frac{n_k}{N} \quad h(k) > 0 \quad (1) \]

\[ N = \sum_{k=0}^{L-1} n_k \quad \text{And} \quad \sum_{k=0}^{L-1} h(k) = 1 \]

Where \( n_k \) denotes the number of pixels with gray level k and N being the total no of pixels in the image. The histogram function can thus be compared with a mix of Gaussian probability functions of the form:

\[ p(x) = \sum_{i=1}^{c} p_i \ast p_i(x) = \sum_{i=1}^{c} \frac{p_i}{\sqrt{2\pi \sigma_i^2}} \exp \left[ -\frac{(x - \mu_i)^2}{2\sigma_i^2} \right] \quad (2) \]

Here \( p_i(x) \) is the probability distribution function of a random variable x of class i, \( p_i \) is the probability of class i and \( \mu_i, \sigma_i \) being the standard deviation of the i th probability distribution function and c is the number of classes within an image with the constraint

\[ \sum_{i=1}^{c} p_i = 1 \quad (3) \]

We calculate the mean square error between the Gaussian mixture and the experimental histogram as the objective function \( f \) Which is to be minimized and from the optimum value of the objective function \( f \) we will obtain the parameters \( p_i, \mu_i, \sigma_i \) for i=1,2,3...c

\[ f = \frac{1}{n} \sum_{j=1}^{n} [p(x_j) - h(x_j)]^2 \quad (4) \]

Here n is total no of pixels of an image.

B. Artificial Bee Colony (ABC) algorithm

1. Initialize the population of solutions, \( x_{ij} \) is the j th parameter of the i th solution.
2. Evaluate the population.
4. Repeat step 1, 2, 3 for required no of food sources.
5. Produce new solutions (food source positions) \( v_{ij} \) in the neighbourhood of \( x_{ij} \) by the employed bees using the formula \( v_{ij} = x_{ij} + \varnothing_{ij} \times (x_{ij} - x_{mj}) \). Here m is the solution in the neighbourhood of i, \( \varnothing \) is a random number in the range [-1, 1].
6. Apply the greedy selection process between \( x_{i} \) and \( v_{i} \).
7. Calculate the probability value \( \text{prob} \) for the solution \( x_{i} \) by means of their fitness values using the equation:

\[ \text{prob}_i = \frac{\text{fit}_i}{\sum_{i=1}^{SN} \text{fit}_i} \quad (5) \]

Here SN is the total no of food sources of a population. In order to calculate the fitness values of the solutions we employed the following equation:

\[ \text{fit}_i = \begin{cases} \frac{1}{1 + |f_i|} f_i > 0 \\ 1 + \text{abs}(f_i) f_i < 0 \end{cases} \quad (6) \]

Normalize \( P_i \) values into [0, 1].

8. Produce the new solutions (new positions) \( v_i \) for the onlooker bees from the solution \( x_i \) selected depending on \( P_i \) and evaluate them.
9. Apply the greedy selection process for the onlookers between $x_i$ and $v_i$.
10. Determine the abandoned solution (source), if exists then replace it with a new randomly produced solution

\[
x_i = \min_j + \text{rand}(0,1) \times (\max_j - \min_j)
\]  

(7)

11. Memorize the best food source position (solution) achieved so far.
13. Until cycle=Maximum Cycle Number(MCN)

C. Implementation of ABC algorithm for image segmentation

![Flow Chart of ABC](image)

**Biological Bee Profile:**

The minimal model for a honey bee colony consists of three classes: employed bees, onlooker bees and scout bees. The employed bees will be responsible for investigating the food sources and sharing the information with recruit onlooker bees. They in turn will make a decision on choosing food sources by considering such information. The food sources having high score (depending on fitness) will have a larger chance to be selected by onlooker bees than those showing lower mark. An employed bees whose food source is rejected due to the low score by employed and onlooker bees will turn into a scout bee in order to support the random search for new food sources. Therefore the exploitation is driven by employed and onlooker bees while the exploration is maintained by scout bees. The implementation details of such bee like operation with the ABC algorithm is described in the next
Initialization:
The algorithm begins by initializing $F_p$ food sources. Each food sources is a $D$-dimensional vector containing the parameter values to be optimized which are randomly and uniformly distributed between the pre specified lower initial parameter bound $x_{j,low}$ and the upper initial parameter bound $x_{j,high}$. Here we have three such parameters $(p, \sigma, \mu)$ which are randomly initialized but considering some restrictions to each parameter (for example $\mu$ must fall between 0 and 255, $p$ is the probability of a pixel class so it must lie between 0 and 1).

$$x_{ij} = x_{j,low} + \text{rand}(0,1) \times (x_{j,high} - x_{j,low})$$

(8)

$j=1, 2, 3, 4, ..., D$ and $i=1, 2, 3, ..., F_p$

With $j$ and $i$ being the parameter and individual indexes respectively.

Employed Bee Phase:
Calculate the fitness function $fit_i$ or the nectar amount for each food source. Memorise the food source with the maximum fitness value say maxfit. Now for each food source select a neighbour of its present position by

$$v_{ij} = x_{ij} + \Theta_{ij} (x_{ij} - x_{mj})$$

(9)

$m=1, 2, 3, ..., F_p$ and $j=1, 2, 3, ..., D$

is a randomly chosen $j$ parameter of the $i$th individual and $k$ is one of the $F_p$ food sources, satisfying the condition $i \neq m$. If a given parameter of the candidate solution $v_i$ exceeds its predetermined boundaries then the parameter should be adjusted in order to fit the appropriate range. The scale factor $\Theta_{ij}$ is a random number between $[-1, 1]$.

Calculate the fitness of the neighbour $fit_j$. If $fit_j > fit_i$, then update the food source with the neighbour source else keep it as it was.

$$fit_i = \begin{cases} 
\frac{1}{1 + abs(f_i)} & f_i > 0 \\
\frac{1}{1 + abs(f_i)} & f_i < 0 
\end{cases}$$

(10)

Onlooker Bee Phase:
Calculate the probability of each food source to be selected by the onlooker bees. For each food source compare the probability of selection with a random no say $R$. If $R < prob_i$ then search for a better neighbour for this food source. If the neighbour is not better than the food source then treat this as a failure for this food source and look for the next food source. After completion of this phase compare the food source with the maximum fitness with the previous maxfit value and choose the better one as the new maxfit.

$$prob_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i}$$

(11)

Scout Bee Phase:
Select the food source with the maximum failure and if it is greater than some previously selected threshold then select the food source as scout and choose a neighbour randomly and replace this food source. Now choose the food source with the maximum fitness and this is the optimal solution.

Selection of Threshold Value:
In order to determine optimal threshold value it is considered that the data classes are organized as $\mu_1 < \mu_2 < \ldots < \mu_D$. Therefore threshold values are obtained by computing the overall probability error of two adjacent Gaussian functions. It is possible to use the following equation to determine the optimum threshold value $T_h$ where

$$A = \sigma_h^2 - \sigma_{h+1}^2$$

(12)

$$B = 2 \times (\mu_h \sigma_h^2 - \mu_{h+1} \sigma_{h+1}^2)$$

(13)

$$C = (\mu_{h+1} \sigma_h)^2 - (\mu_h \sigma_{h+1})^2 + 2 \times (\sigma_h \sigma_{h+1})^2 \times \ln \left( \frac{\sigma_{h+1} \mu_h}{\sigma_h \mu_{h+1}} \right)$$

(14)

III. FCM BASED SEGMENTATION

- Fuzzy C Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. It is based on minimization of the objective function.
- The aim of FCM is to find cluster centres that minimize a dissimilarity function. The membership matrix $U$ is randomly initialized as:
\[
\sum_{i=1}^{c} u_{ij} = 1 \quad j=1, 2, 3\ldots n \quad (15)
\]

- The dissimilarity function that is used in FCM is given as:

\[
J(U, c_1, c_2 \ldots c_c) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij} m d_{ij}^2
\]

Here value of \(u_{ij}\) is between [0,1], \(c_i\) is the centre of the \(i\) th cluster, \(d_{ij}\) is the Euclidean distance between \(i\) th centre and \(j\) th data point and value of \(m\) is between [1,\(\infty\)] is a weighting exponent.

- To reach a minimum of dissimilarity function there are two conditions. These are given below

\[
c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}
\]

\[
u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{m-1}}
\]

- So the pseudo code for FCM is as follows:
  1. Randomly initialize the membership matrix \(U\) according to equation 15.
  2. Calculate centre \((c_i)\) by using equation 17.
  3. Compute dissimilarity between the centres and the data points using equation 16. Stop if it’s improvement over previous iteration is below a threshold.
  4. Compute a new \(U\) using equation 18. Go to step 2.

IV. EXPERIMENTAL RESULTS

Experimental results show image segmentation using ABC algorithm. Here the mixture parameters \((\beta, \sigma, \mu)\) are obtained from the objective function after applying ABC algorithm. Here the experiment starts with 10 food sources \((F = 10)\). Each food source can be represented as follows:

\[
F_1 = p_1, \sigma_1, \mu_1, p_2, \sigma_2, \mu_2, p_3, \sigma_3, \mu_3
\]

The parameters are randomly initialized but with some restriction as mentioned before. Experimental results for multiple images shown below
Validity Index Measure:

Table 1: Cameraman

<table>
<thead>
<tr>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Class 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Davies-Bouldin</td>
<td>3</td>
<td><strong>1.2000</strong></td>
<td>3.3333</td>
</tr>
<tr>
<td>Xei-Beni</td>
<td>.6823</td>
<td><strong>.0758</strong></td>
<td>1.4925</td>
</tr>
<tr>
<td>β-value</td>
<td>5.1796</td>
<td><strong>6.7355</strong></td>
<td>5.4422</td>
</tr>
</tbody>
</table>

Table 2: Bubble

<table>
<thead>
<tr>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Class 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Davies-Bouldin</td>
<td>2</td>
<td>2.8000</td>
<td>2.3333</td>
</tr>
<tr>
<td>Xei-Beni</td>
<td><strong>.4906</strong></td>
<td>6.2538</td>
<td>.5263</td>
</tr>
<tr>
<td>β-value</td>
<td><strong>2.7712</strong></td>
<td>2.7133</td>
<td>2.4925</td>
</tr>
</tbody>
</table>

Table 3: Lake

<table>
<thead>
<tr>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Class 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Davies-Bouldin</td>
<td><strong>1.5000</strong></td>
<td>2.6000</td>
<td>3.1667</td>
</tr>
<tr>
<td>Xei-Beni</td>
<td>.09139</td>
<td>1.0759</td>
<td>1.0443</td>
</tr>
<tr>
<td>β-value</td>
<td><strong>8.1790</strong></td>
<td>5.8611</td>
<td>5.4422</td>
</tr>
</tbody>
</table>

Table 4: Jet Plane

<table>
<thead>
<tr>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Class 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Davies-Bouldin</td>
<td><strong>.5000</strong></td>
<td>1.2000</td>
<td>3.3333</td>
</tr>
<tr>
<td>Xei-Beni</td>
<td><strong>.0729</strong></td>
<td>1.6178</td>
<td>1.6061</td>
</tr>
<tr>
<td>β-value</td>
<td><strong>4.5138</strong></td>
<td>3.8046</td>
<td>4.4220</td>
</tr>
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</table>

Table 5: Lena

<table>
<thead>
<tr>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Class 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Davies-Bouldin</td>
<td>2.5000</td>
<td>1.2000</td>
<td><strong>1</strong></td>
</tr>
<tr>
<td>Xei-Beni</td>
<td>.2631</td>
<td>.0130</td>
<td><strong>.0075</strong></td>
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<tr>
<td>β-value</td>
<td>1.5806</td>
<td>4.6147</td>
<td>5.1951</td>
</tr>
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</table>

Table 6: Mandrill

<table>
<thead>
<tr>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Class 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Davies-Bouldin</td>
<td>1.2500</td>
<td><strong>.8000</strong></td>
<td>.8333</td>
</tr>
<tr>
<td>Xei-Beni</td>
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<td><strong>.2803</strong></td>
<td>.3591</td>
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<tr>
<td>β-value</td>
<td>2.3884</td>
<td>3.0017</td>
<td><strong>3.5231</strong></td>
</tr>
</tbody>
</table>
Medical and Satellite Image Segmentation Using ABC in Comparison with FCM:

- Figure 23 is a sagittal transaction through the human brain.
- Description (860.860 pixels, file size: 70 KB, MIME type: jpeg).
- Here the difference between the image segmented with FCM and the image segmented with ABC can be visualized and also pointed out with arrow in the above image.
- We can see that the result obtained by ABC is much better as very small regions can be viewed clearly in comparison with FCM.

- Figure 26 is an anonymous clinical image.
- Description: (900, 1119 pixels, file size: 390 KB, MIME type: jpeg).
- This image (26) was converted from DICOM acquisition format into jpeg format.
- In the original image (26) there is two black spots in the centre position. After segmentation with FCM these two spot is not visible for FCM but they are visible in the image segmented by ABC.
- Here the result is compared for both FCM and ABC considering same no of classes.

- This image (fig29) was captured by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA’s terra satellite on September 21, 2003.
- This image shows a cloud of volcanic ash (tan pixels) over Kodiak Island, Alaska created by strong winds that picked up and loose volcanic ash.
- If the volcanic eruption is strong enough it will inject material into the stratosphere, more than 10 miles above the earth’s surface.
The centre position of the segmented image by ABC shows three different shades (shown by arrow) of gray but the image segmented by FCM shows only two shades of gray at the centre position.

**Band Image Segmentation Using ABC:**

- Figure 32: band1
- Figure 33: band2
- Figure 34: band3
- Figure 35: band4
- Figure 36: combined histogram
- Figure 37
- Table 7
- Figure 38: Error Plot of Band4 Image
- Figure 39: Segmented Band3 Image
- Figure 40: Segmented Band4 Image

<table>
<thead>
<tr>
<th>Index</th>
<th>Class1</th>
<th>Class2</th>
<th>Class3</th>
<th>Class4</th>
<th>Class5</th>
<th>Class6</th>
<th>Class7</th>
<th>Class8</th>
<th>Class9</th>
<th>Class10</th>
<th>Class11</th>
<th>Class12</th>
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<tbody>
<tr>
<td>Davies- bouldin</td>
<td>3.2087</td>
<td>1.2010</td>
<td>1.5000</td>
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<td>1.1111</td>
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<td>1.050</td>
<td>1.2017</td>
<td></td>
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<tr>
<td>Rel. Entropy</td>
<td>.5074</td>
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<td>.1522</td>
<td>.6682</td>
<td>.1329</td>
<td>.0199</td>
<td>.0666</td>
<td>.3295</td>
<td>.3666</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
IRS-1A Calcutta image was acquired by Indian Remote Sensing Satellite. The image used here is taken from Linear Imaging Self Scanner (LISS-II). LISS-II has a spatial resolution of 36.25 m, 36.25 m and the wavelength range 0.45 to 0.86 µm. The whole spectrum range is decomposed into four spectral bands namely blue, green, red and near infrared (NIR) corresponding to band1, band2, band3, band4 having wave length 0.45 to 0.56 µm, 0.52 to 0.59 µm, 0.62 to 0.68 µm, 0.77 to 0.86 µm respectively.

The original images have poor illumination and very low contrast so they are not properly visible. Therefore the histogram of all of these band images is combined (fig36).

Figure37 shows the combined histogram approximated by Gaussian mixture model.

- The optimum result is obtained with 10 classes.
- Figure38 shows the plot of error value (the difference between Gaussian mixture model and the combined histogram). Here the values of X-axis that is 1, 2 ......9 shows class4, class5, class12 respectively.
- Figure39 and Figure40 both are segmented with class10.
- We can see from error plot that optimum result is obtained for class 10.
- Optimum result is again compared by taking some validity indices which is shown below.
- Table7 consists of three cluster validity indices Davies-Bouldin [11], Xei-Beni [12], β-values [18] and each of these indices is taken for class4 to class12. Optimum result is obtained for each of the three indices for class10.

V. CONCLUSION

In this paper automatic image segmentation with multi threshold approach based on ABC algorithm is proposed. The segmentation process is approached as an optimization problem. The algorithm approximates the 1-D histogram of a given image using a GMM whose parameters are calculated with ABC algorithm. Each Gaussian function approximating the histogram represents a pixel class and therefore one threshold point. Experimental evidence shows that ABC algorithm has an acceptable compromise with respect to its convergence, its computational cost, time in comparison to other proposed method like FCM.

VI. FUTURE WORK

Satellite image segmentation is very difficult. In order to improve the satellite image segmentation we will concentrate on texture detection which is not possible with ABC algorithm. So that we can have a density based approach for satellite image segmentation.

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REFERENCES

BIOGRAPHY

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**Ankita Bose** is presently doing M.Tech in University of Kalyani. She has received B.Tech Degree from West Bengal University of Technology in the year 2010. Her main areas of interest are image segmentation, soft computing and pattern recognition.