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# Multilevel image segmentation using ABC algorithms

[1]Chaya P, [2]Chaithra K, [3]Harshitha C, [4]Sushma N, [5]Thanushree GN

[1]Assistant Professor [2,3,4,5] Student

Department of Information Science and Engineering

[1, 2,3,4,5] GSSS Institute of Engineering and Technology for Women, Karnataka, India.

**Abstract**: Multilevel thresholding is an important technique for image processing. To find the optimal values in an acceptable computation time, meta-heuristic optimization algorithms have shown promise to reduce time-complexity, especially the Artificial Bee Colony (ABC) algorithm which mimics honeybee foraging activities. In this project, we propose ABC as the optimizing algorithm to address the issue of time complexity in Otsu's multilevel image thresholding process and improve image quality at higher dimensionality.

**Index Terms – Artificial bee Colony(ABC) Algorithm.**

## I. INTRODUCTION

Computer vision envisages image thresholding as one of the key image pre-processing tasks. It has a large number of applications, from satellite imaging, document processing to medical diagnostics. The process of image thresholding involves separating object classes from the background of an image by comparing each pixel with an appropriately chosen threshold value t, which denotes the color pixel intensity. An efficient image thresholding technique is one, which not only segments in terms of quality of images, but also does this efficiently within acceptable computation time.

In practice, thresholding process can be classified into two types (a) bi-level or (b) multilevel thresholding. When binary images are created from gray scale images considering the fact that only two classes (objects and background) exists in an image, it is called as Bi-level thresholding. When an image is divided into multiple gray level using multiple thresholds, then it is termed as multilevel thresholding. Multilevel thresholding too has been an active research topic, but for an optimal solution the algorithms get trapped in exhaustive search without convergence. This increases time complexity which increases exponentially.

The main objective of the project is to:

- To design and develop a new approach for optimization of the maximum entropy problem based on the Artificial Bee Colony (ABC) algorithm.
- To design a novel methodology using Artificial Bee colony (ABC) algorithm as the optimizing algorithm to address the issue of time complexity in Otsu's multilevel threshold process.
- To study the literature on multilevel thresholding, various optimization techniques, their evaluations and their respective performances, algorithms used their limitations and difficulties.

## II. LITRTURE REVIEW

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper Do not number text heads—the template will do that for you. Finally, complete content and organizational editing before formatting. Please take note of the following items when proof reading spelling and grammar returns of the shares and estimated betas.[1] " Fast three-dimensional Otsu thresholding with shuffled frog- leaping algorithm" This paper describes Gaussian distribution, window technique and spatial probability distribution and to find an estimate of the parameters of Gaussian distribution that best fits the histogram and integrated the histogram with the Parzen window technique to estimate the spatial probability distribution [2] "A multi-level thresholding approach using a hybrid optimal estimation algorithm " This paper approximated the histogram with a mixed Gaussian model, and estimated the parameters with a hybrid algorithm based on particle swarm optimization and expectation maximization.[3] "Optimal multithresholding using a hybrid optimization approach" this paper resolves the histogram Gaussian fitting problem and fitted the Gaussian curve by Nelder-Mead simplex search and particle swarm optimization. To resolve the histogram Gaussian fitting problem [4] "Non-supervised image segmentation based on multiobjective optimization" this paper resolve the histogram Gaussian fitting problem, used an improved variant of simulated annealing adapted to continuous problems. [5] "A multi-scale framework for adaptive binarization of degraded document images" it find the thresholds that separate the gray-level regions of an image in an optimal manner and Non-parametric approaches find the thresholds that separate the gray-level regions of an image in an optimal manner based on some discriminating criteria. Otsu's criterion, which selects optimal thresholds by maximizing the between class variance, is the most popular method.

## II METHODOLOGY

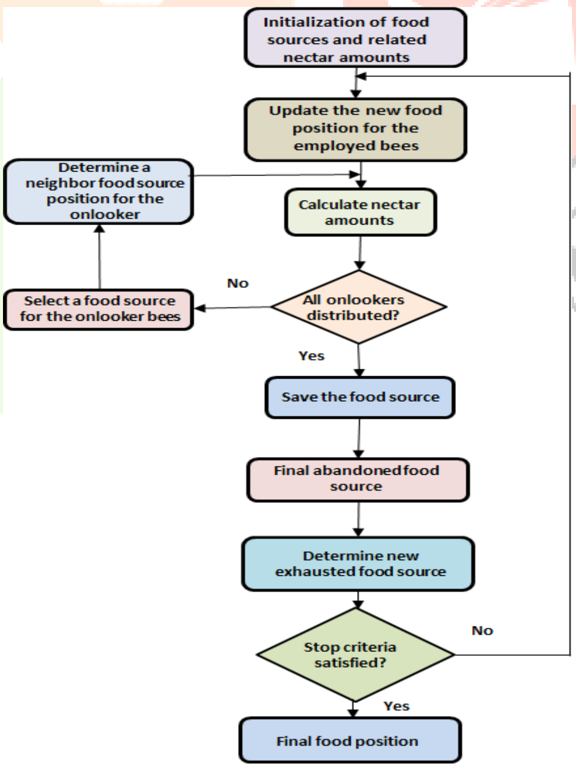


Fig 1: ABC Algorithm flow-chart

We use the Artificial Bee colony (ABC) algorithm (Fig 1) which mimics the honey bee in their natural colonies. Three groups of bees can be found in a colony

1. The "employed bees"
2. The "onlooker bees and" and
3. The "scout bees"

Employed bees are assigned to sources of food and they evaluate their nectar amount. Scout bees abandon the poor food sources by stopping the exploitation process and discover new random sources of food. The best food sources found till now are memorized.

Above procedure is carried out continuously till such time a required output is achieved or the maximal no. of runs are completed. No. of sources of food is equal to the "employed bees" count which directly equates to possible solutions to the problem. "Bees" waiting on dance floor inside the hive are called onlooker bees. In the first cycle employed bees move to random sources of food and the nectar amount is evaluated. Employed bees share the food information and its associated nectar value or fitness value with onlookers.

Onlookers make decision of food position basis the nectar information brought by employed bees. Onlooker use greedy method to update their position.

In the next cycle employed bee chooses new source of food which lies in the neighbourhood of the source of food found in the previous cycle by referring to its memory and compares by evaluating the nectar amount. Onlookers use this information and select sources of food based on its nectar value. The probability of selecting a position increases when the amount of the nectar gets higher. Both employed and onlooker bees search for better food positions in each cycle. When the nectar amount of a source of food is not improved in the limited number of cycles then bees abandon these food source positions. "Unemployed bees" also Exploitation of nectar in sources of food is carried out by "employed bees" and "onlooker bees". In each cycle, the source of food with best present nectar quality is memorized. This position of the food with best nectar value represents local optimum solution in one cycle. This search process of sources of food by employed bees, onlooker bees and scouts is performed in maxi cycles. Finally, the best of all the global solutions obtained in all the cycles gives the optimum solution

**Proposed System**

Otsu proposed to either maximize the between-class variance or minimize the within-class variance and select that gray-level as the threshold candidate. Its input is the gray level histogram (e.g. 0,256)

Consider a gray scale image f(x, y) of size H x W pixels with L intensity levels (peppers.png used in our research)

Along with each onlooker bee, a probability Pi is assigned that is proportional to the quality of source food it chooses.

It is calculated using the following formula (1):

$$P_i = \frac{f_i}{\sum_{i=1}^{S} f_n} \qquad (1)$$

A new candidate position is produced from existing memory. It is represented as expression (2):

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{oi}) \qquad (2)$$

To abandon a source of food, control parameter B is used. Sources of food are abandoned when pre-determined trials (T) > B. Scout bees are then generated. New sources of food are found by Scout bees and update existing food positions randomly using below equation (3):

$$x_i^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j) \qquad (3)$$

Since threshold-based image segmentation is a multidimensional discreet optimization problem posed, for fitness evaluation of t threshold level candidates, the Otsu thresholding Method is used.

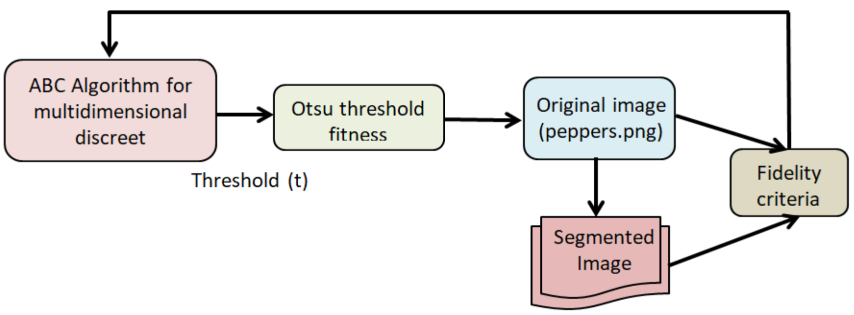


Fig 2: Optimization process

Weighted within-class variance is defined as:

$$\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t) \quad (4)$$

Class probabilities:

$$q_1(t) = \sum_{i=1}^{t} P(i);\ q_2(t) = \sum_{i=t+1}^{L} P(i) \quad (5)$$

class means:

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)};\ \mu_2(t) = \sum_{i=t+1}^{L} \frac{iP(i)}{q_2(t)} \quad (6)$$

The individual class variance is:

$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{q_1(t)} \quad (7)$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{L} [i - \mu_2(t)]^2 \frac{P(i)}{q_2(t)} \quad (8)$$

The PSNR equation is as follows:

$$PSNR = 10 * Log_{10}[(Max^2 * m * n)/ \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (I(i,j) - K(i,j))^2] \quad (9)$$

**CONCLUSION AND FUTURE SCOPE**

This model can be used for major fields like medical and agriculture where image searching and retrieval from the large database can be done efficiently**.**

This proposed model can be used in major domains like Agriculture (plant disease, land surveys), Medical imaging, Defence, Smart City etc.0 where thresholding plays a major role in distinguishing the image objects from its background and multilevel thresholding helps in separating the images into several different regions.

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