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OABC: An Otsu-Artificial Bee Colony Multilevel Image Threshold Optimization for Liver Tumor Segmentation

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Abstract

Grey scale or color image conversion involves thresholding technique which can be either at single or multiple threshold levels. Resultant images have reduced pixel level classes. As level of thresholding required increases, the process becomes complex involving exhaustive search and thereby increasing computational resources and time complexity. Meta-heuristic optimization algorithms show promise to reduce time-complexity, especially the Artificial Bee Colony (ABC) algorithm mimicking honeybee foraging activities. It provides optimal results when sampling a large solution space. Since threshold-based image segmentation is a multidimensional discreet optimization problem, for fitness evaluation of threshold level candidates, Otsu's thresholding method has been widely employed. In this paper, proposed is an Otsu-ABC multilevel image thresholding model for CT images using MATLAB for Liver tumor segmentation. The developed model is evaluated for increased dimensionality and computation time. It is also benchmarked against other commonly used algorithms. Results demonstrate that the proposed model is immune to dimensionality increase and outperforms all other models with regards to quality of images segmented and computation time proving that the model is ideal for optimizing multilevel image thresholding problems involving large thresholds for complex computer vision problems in medical diagnostics, biometrics, surveillance, satellite imagery and gaming.

Category: Smart and intelligent computing
Keywords: Artificial Bee Colony algorithm; Otsu thresholding; Meta-heuristics

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, biometrics, surveillance, gaming to medical diagnostics [1]. The process of image thresholding involves separating object classes from background

of an image by comparing each pixel with an appropriately chosen threshold value *t*, which demotes the color pixel intensity [2]. 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 is of two types (a) bi-level or (b) multilevel thresholding. When binary images are created from a gray scale image considering the fact that only two classes (objects and background) exist in an image, then it is termed as bi-level thresholding. An image divided into multiple gray levels using multiple thresholds, then it is termed as multilevel thresholding [3]. It is bi-level thresholding that has evoked a lot of interest among researchers over the past decade [4-5]. They have also taken into consideration the work by Otsu [6]. Multilevel thresholding too has been an active research topic [7], but for an optimal solution the algorithms get trapped in exhaustive search without convergence. This increases time complexity which increases exponentially [8]. For finding a solution that returns optimal values within computation times which are reasonable, alternate optimization algorithms have been used by researchers like “honey-bees mating optimization” (HBMO), particle swarm optimization (PSO), Firefly etc. Mostly, these solutions have been successful to reduce time complexity and improve image quality to some extent, but there is further scope for improvement. In the recent past, the problem of exhaustive search in multilevel thresholding has been tackled by population-based optimization techniques. However, optimization of the maximum entropy problem now has an innovative approach which is entirely established on the “Artificial Bee Colony” (ABC) algorithm. This paper proposes ABC algorithm to choose optimum thresholds in a multilevel image by addressing the issue of time complexity in Otsu fitness function and improve CT image segmentation quality at higher dimensionalities.

Rest of the sections of the manuscript are divided as follows: Section II discusses related works pertaining to recent meta-heuristic attempts at multilevel image thresholding. Section III explains the system design, section IV presents the results followed by section V discussion, section VI conclusion and references at the end.

II. LITERATURE SURVEY

Literature has many image thresholding related research publications. At a broad level, there are two approaches towards thresholding, divided into parametric and non-parametric methodology. In the first case, each group consisting of grey-level distribution follows a Gaussian distribution and the parametric method then tries to estimate a histogram best fitting the Gaussian distribution. Authors in [9] used the parzen window methodology in the histogram to find spatial probability distribution. Authors in [10] used a novel technique to estimate the parameters in an approximated histogram with a mixed Gaussian distribution by using a hybrid implementation of PSO and expectation maximization (EM) algorithms. Authors in [11] used a combination of “Nelder-Mead simplex” search and PSO to fit the Gaussian curve. Authors in [12] used an enhanced version of simulated annealing algorithm to find a solution for the histogram Gaussian fitting problem.

In the case of non-parametric methodology, they select thresholds on the basis of optimally chosen grey-levels by some discriminating criteria in an image. One such popular criterion was proposed by Otsu [13] which maximized between class variance to select optimal threshold levels. However, when we encounter multilevel image thresholding problems, inefficiently formulated between class variance results in time-complexity. Many researches have been proposed to tackle this issue. Authors in [14] proposed a fast implementation using heap and quantization-based data structure. Authors in [15] proposed a two-stage multi-threshold Otsu method. Authors in [9] proposed an enhanced shuffled frog-leaping algorithm to the three-dimensional Otsu thresholding. Authors have also investigated other criteria apart from maximizing the between class variance. Authors in [16] used the “maximum entropy thresholding” (MET) criterion with HBMO optimization algorithm for fast thresholding. Authors in [17] used the “minimum cross-entropy thresholding” (MCET) along with a recursive programming technique which resulted in drastic reduction of computation time in MCET objective function. Authors in [18] proposed a non-extensive information-theoretic parameter called Jensen-Tsallis divergence for image edge detection.

It is a known fact that computation time increases drastically as the number of threshold values increase. Therefore, the classical exhaustive method (ES) fails. For example, in a 4-level thresholding of a Lena image which is of size 512x512, more than three days are taken for computing the thresholds [16]. Hence, researchers have opted for nature inspired Computational Intelligence (CI) algorithms to find optimum threshold values in the least time. Authors in [19] and [20] proposed an innovative image thresholding model based on multi-objective optimization and used a feature-curated GA and PSO respectively to solve the model. But the efficiency of both these algorithms is poor.

Dervis Karaboga [21] proposed the ABC algorithm in 2005 inspired by the natural foraging behavior of honeybees. Comparing it with other nature inspired algorithms, its performance w.r.t. function optimization is found to be many notches higher than GA, DE, PSO and others [22]. The main reason for this is the no. of searches per iteration. Only one search option is performed per iteration for most of the universal optimization techniques. For example, in PSO algorithm, one global search in the beginning and a local search at the end stage are carried out. However, ABC algorithm performs a global search in addition to the local search thereby increasing the probability of finding an optimum result as it prevents local optima [23]. Hence, it is advantageous and our choice in this research.

III. SYSTEM DESIGN

A. Materials and Method

Transverse CT images of patients (courtesy local diagnostics lab) are considered with histologically proven liver tumors and parameter settings as indicated in Table 1.

Table 1. Parameters considered for CT image

Parameter	Setting
Tube voltage	120KV
Tube current	200, 240mA
DFOV	30, 36cm
Slice thickness	5, 10mm

Post the intravenous injection, used as a contrast agent, the scans are carried out. The radiologist confirmed presence of liver tumor from manual inspection. Digitization of these CT images are carried out using a X-ray film digitizer to get a 2048x2500 resolution and 12-bit gray scale digitized image. We use Microsoft Visual C++ and MATLAB in Win environment as a CAD environment, where the above digitized image is converted into a portable gray map (.pgm) file format for use in this research.

B. ABC Algorithm

We employ the ABC algorithm which mimics the honey bee in their natural colonies as a feature selection tool for choosing optimal threshold values *t* for image segmentation. As part of their natural foraging behavior, honeybees demonstrate communication, co-ordination and self-organization skills [24]. Communication is via a mechanism called ‘waggle dance’, which is used effectively to lure other bees to new and other lucrative sources of food. Here, a swarm of ‘S’ bees (called population) is created. Possible solutions are represented by food sources that are assigned to the bees in a *'D'*-dimensional space, which basically corresponds to the no. of parameters in the optimization problem. Fitness is a measure of nectar quantity at a source of food. Three groups of bees can be found in a colony, the employed bees (EB), the onlooker bees (OB) and the scout bees (SB).

In every cycle and for all the three categories of bees, the algorithm consists of the following steps:

1: EB are assigned to sources of food and they evaluate their nectar amount.

2: EB share the information of these sources of food with a probability value to OB's and they are placed on the sources of food after evaluating their amount of nectar

3: SB's abandon the poor food sources by stopping the exploitation process and discover new random sources of food.

4: 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 is completed. No. of sources of food is equal to the EB count which directly equates to possible solutions to the problem. Bees waiting on dance floor inside the hive are called OB. In the first cycle EB move to random sources of food and the nectar amount is evaluated. EB share the food information and its associated nectar value or fitness value with OB. OB's make decision of food position basis the nectar information brought by EB. OB's use greedy method to update their position. In the next cycle EB chooses new source of food which lies in the neighborhood of the source of food found in the previous cycle by referring to its memory and compares by evaluating the nectar amount. OB's 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 EB and OB 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. A new source of food is created randomly and assigned to bees known as SB. Thus, SB's get generated to randomly create new sources of food. Since the OB and SB do not work initially, they are also called unemployed bees (UB). Exploitation of nectar in sources of food is carried out by EB and OB. 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 EB, OB and SB is performed in K_{max} cycles. Finally, the best of all the global solutions obtained in all the cycles gives the optimum solution.

1) Initialization step: Here, the control parameters of the algorithm are initialized, like population, dimension, maximum cycles $\boldsymbol{k_{max}}$, and the limits- both upper and lower $(\boldsymbol{x_{min}}, \boldsymbol{x_{max}})$. Also, another *Limit (B)* is set which is for abandoning a source of food if it cannot be further improved or exploited.

The EB then searches its neighborhood by applying greedy selection criteria to choose between its current source of food and one in the neighborhood. If the new source of food is better, it refreshes x_{iD} and doesn't update it otherwise.

2) Onlooker step: Along with each OB, a probability *Pi* is assigned that is proportional to the

Table 2. ABC algorithm initialization values

Parameter	Number	Remarks
Population (S)	30	Max. population of bees
Food no.	15	# of sources of food. ~50% of population
Limit (B)	100	Max. limit after which source of food abandoned & cannot be further improved
# of iterations	100	# of foraging cycles
Dimension	2	Optimization parameter count that needs to be optimized
Runtime	25	# of runs in order to see its

robustness

to the quality of source food it chooses. It is calculated using the following formula (1):

$$\boldsymbol{P_i} = \frac{\boldsymbol{f_i}}{\sum_{i=1}^{s} \boldsymbol{f_n}} \quad (1)$$

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

$$v_{ik} = x_{ik} + \epsilon_{ik}\,(x_{ik} - x_{oi}) \quad (2)$$

$o = \{1,2,3, \ldots N\}; (o \neq i);$ k={1,2,3,…D} are randomly assigned values. ϵ_{ik} is a number randomly chosen between the two values [-1, 1]. If the value of the new solution exceeds x_{min} and x_{max}, then their values are set to acceptable limits. Fitness is then evaluated.

3) Scout Step: To abandon a source of food, control parameter *B* is used. Sources of food are abandoned when pre-determined trials *(T) > B*. SB's are then generated. New sources of food are found by SB and update existing food positions randomly using below equation (3):

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

Table 2 lists the various parameters and the algorithm initializing values. Fig. 1 depicts the complete flow-chart of the ABC algorithm.

C. Image Segmentation

Since threshold-based image segmentation is a multidimensional discreet optimization problem posed, for fitness evaluation of *t* threshold level candidates, the Otsu thresholding Method [6] is used.

Otsu proposed an approach 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)

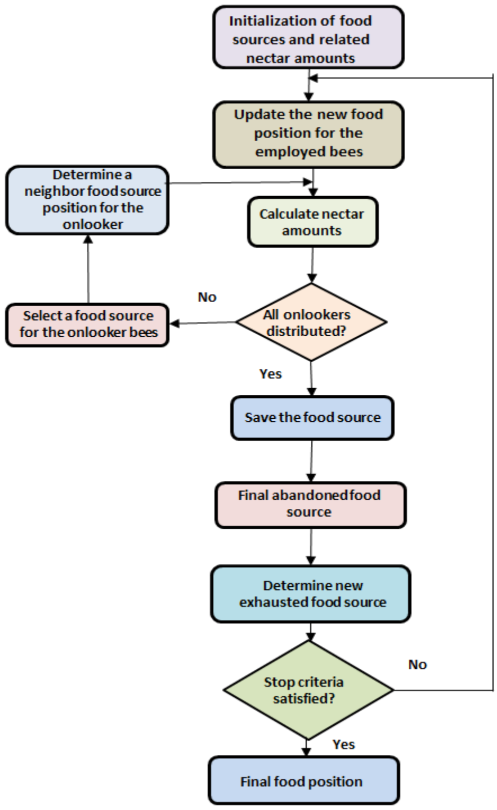

Fig. 1. ABC algorithm flow-chart

Consider a gray scale image f(x, y) of size H x W pixels with L intensity levels (Liver tumor CT image used in proposed model). Then

The weighted within-class variance is defined as:

$$\sigma_{wc}^2(t) = r_1(t)\sigma_1^2(t) + r_2(t)\sigma_2^2(t) \quad (4)$$

The weighted between-class variance is defined as:

$$\sigma_{bc}^2(t) = r_1(t)r_2(t) + (\mu_2(t) - \mu_2(t))^2 \quad (5)$$

And class probabilities is defined as:

$$r_1(t) = \sum_{i=1}^{t} P(i);\ r_2(t) = \sum_{i=t+1}^{L} P(i) \quad (6)$$

Class means:

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{r_1(t)}\ ;\ \mu_2(t) = \sum_{i=t+1}^{L} \frac{iP(i)}{r_2(t)} \quad (7)$$

The individual class variance is:

$$\sigma_1^2(t) = \sum_{i=1}^{t}[i-\mu_1(t)]^2 \frac{P(i)}{r_1(t)} \quad (8)$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{L}[i-\mu_2(t)]^2 \frac{P(i)}{r_2(t)} \quad (9)$$

D. Simulation procedure

The above discussed Otsu function is optimized using ABC algorithm in MATLAB. An exhaustive sequential search for a threshold level t^* is performed satisfying the equation:

$$\sigma_b^2(t^*) = \max_{1 \le t \le L} \sigma_b^2(t)\,;\, t \in [1,256] \quad (10)$$

i.e. it maximizes the weighted between-class variance. Fig. 2 depicts the complete OABC model.

While comparing with contemporary models, "*Peak Signal-to-Noise Ratio (PSNR)*" criteria is used which is a very commonly used performance parameter. PSNR denotes the ratio of maximum signal power to the corrupted noise power [25]. A higher PSNR signifies better quality of image

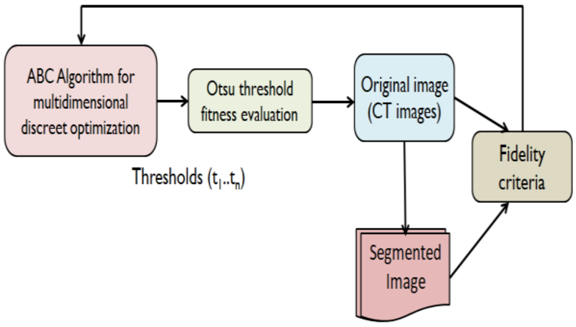

Fig. 2. The OABC model

threshold value. The PSNR equation is stated as follows:

$$PSNR = 10 * Log_{10}[(Max^2 * c * d) / \sum_{i=0}^{c-1}\sum_{j=0}^{d-1}(I(i,j) - K(i,j))^2] \quad (11)$$

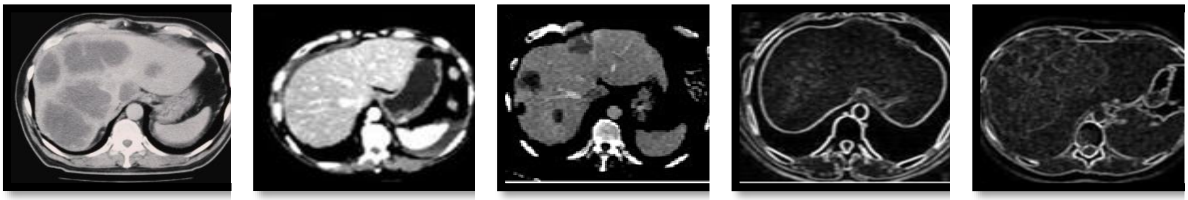

Fig. 3. Consolidated results to see effect of dimensionality on image segmentation

Table 3. Dimensionality study results

Image: Liver CT images (.pgm) ; # of trials: 10; dimensionality (Dim)=2,4,6,8				
Parameter	Dim:2	Dim:4	Dim:6	Dim:8
Optimal threshold values	[83,151]	[80,83,151,195]	[14,83,112,151,152,237]	[27,60,83,135,151,158,220,236]
Time taken	0.0084 sec	0.0085 sec	0.0087 sec	0.0099 sec
Mean	1.897x103	1.8969x103	1.8965x103	1.8969x103
Standard deviation	1.3548	3.1911	2.80	2.3329

IV. RESULTS

A. Otsu-ABC results and effect of higher dimensionality

We use the ABC algorithm to select optimal thresholds for Otsu function. Fig.3 shows the original image, images after multi-thresholding and the effect of increasing complexity or dimensionality on image quality. Table 3 enumerates the results of the various dimensionality runs and other details like time taken, mean and standard deviation. Figs. 4-7 show the number of iterations to convergence plot using the proposed model from MATLAB.

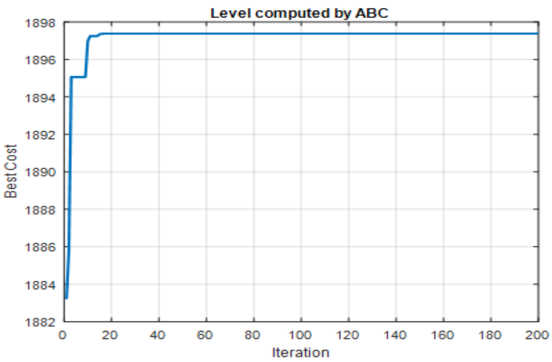

Fig. 4. Convergence plot (d=2)

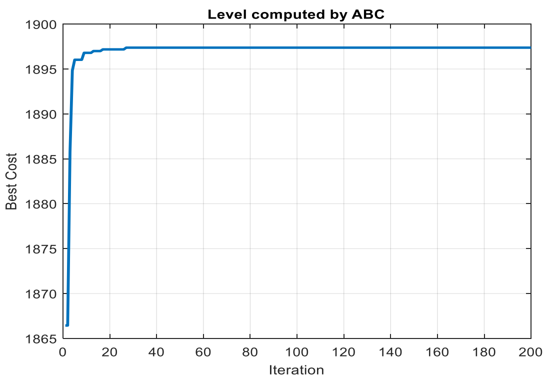

Fig. 5. Convergence plot (d=4)

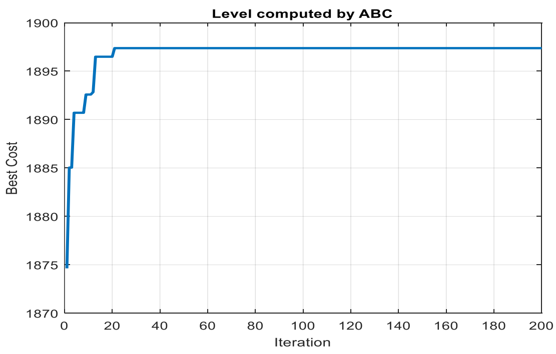

Fig. 6. Convergence plot (d=6)

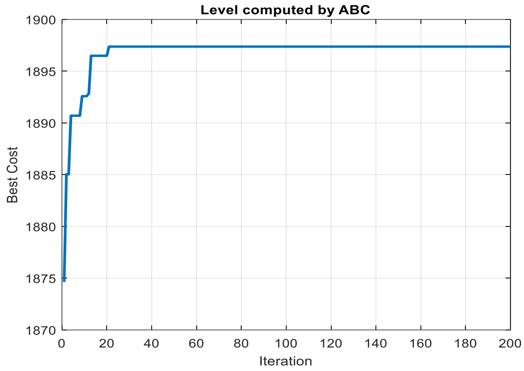

Fig. 7. Convergence plot (d=8)

Basis the results obtained, it is seen that the performance of OABC model is good in terms of time complexity, convergence and tumor segmentation quality.

We next study the scaling characteristics and Fig.8 shows a plot for the same.

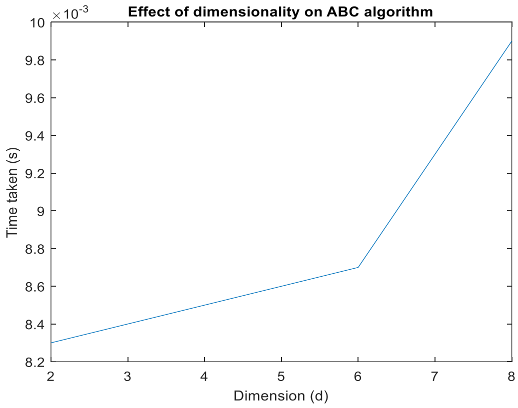

Fig. 8. Effect of dimensionality on OABC algorithm

In general, OABC model showed excellent performance in all the test cases. Its scaling behavior was unaltered with sustained performance even when the degree of complexity, in terms of optimization parameters was increased. Overall, we see the following advantages:

1) The execution time increases linearly with the increase in optimization parameters
2) Since the value of standard deviation decreased over various runs, it can be

inferred that the algorithm stability increased with increasing degree of complexity

3) ABC is very simple and flexible and scores over other population-based algorithms by using lesser no. of control parameters. We don't require tweaking extraneous parameters like mutation, cross over rate etc. like in other Computational Intelligence (CI) algorithms.

B. Inter-model comparison

Here we compared the proposed model with other proposed models using PSO and Exhaustive search algorithms. It is observed that PSNR value increased as the threshold levels increased. The proposed Otsu-ABC method returns the best results as shown in Fig. 9.

We also need to consider the time-complexity. It is seen that the computation time increases with threshold levels. Fig. 10 shows that the proposed model was faster for multilevel thresholding.

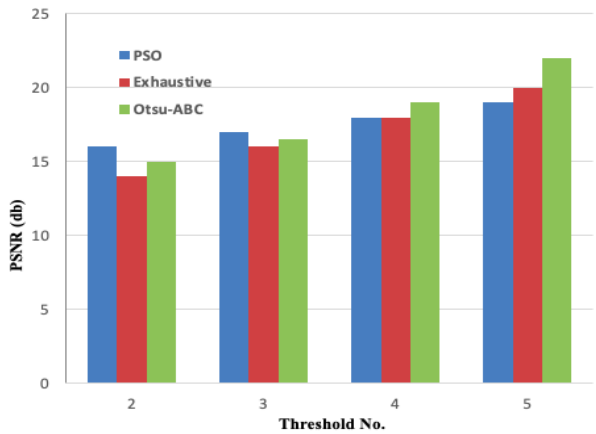

Fig. 9. PSNR comparison with other models

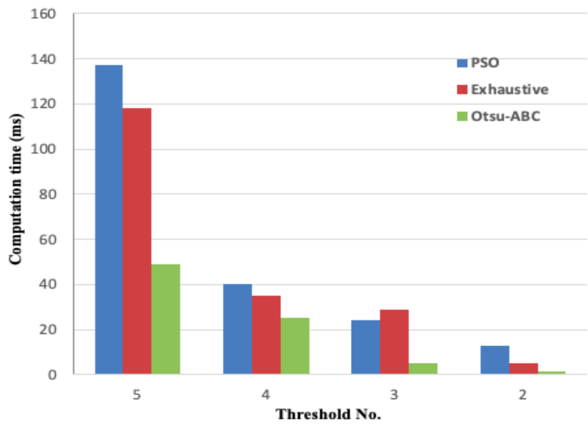

Fig. 10. Computation time comparison to segment CT image

V. DISCUSSION

Initially, development of the standardized version of ABC algorithm was put to use for only mathematical optimization problems. However, by suitably modifying the same it was enhanced to solve a wider variety of problems, from constrained to unconstrained problems. A lot of research comparing its performance with other CI paradigms has been carried out, including combining it with exact solutions to overcome any limitations or solve certain classes of problems. And in most cases, its performance has been the best in terms of its speed, robustness and performance.

With the results obtained, where it has been used to extract features i.e. the optimal threshold values for the Otsu fitness function, we can conclude that OABC model holds a great promise to be applied to complex, field-scale optimization problems. It can be used in both standalone and hybrid modes with other popular approaches to increase speed and efficiency to address real-time problems of higher dimensionalities.

VI. CONCLUSION

The paper addresses to solve the maximization problem using a combination of Otsu-ABC optimization technique. For thresholding multilevel grey images, Otsu criterion has proved its mettle over the years. The approach maximizes the between-class variance for multilevel image segmentation. The results demonstrate that OABC model is very efficient when we consider the algorithm run-time, convergence and the image segmentation quality obtained. In the dimensionality test, which is carried out by increasing the complexity of runs, it was found that the proposed model performed exceedingly well in all test cases. Its scaling behavior was unaltered and it sustained its performance even when the degree of complexity was increased. The results encourage future research by applying OABC for complex computer vision problems in medical diagnostics, biometrics, surveillance, satellite imagery and gaming.

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