Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

Multi-Otsu's image segmentation for Mammograms using Artificial Bee Colony (ABC) Algorithm

Mamindla Ajay Kumar [1], Dr. Y Ramadevi [2]

[1]Research Scholar, OU., Department of CSE, GCET.
Ajaymamindla.cse@gcet.edu.in
[2]Department of CSE, CBIT, Hyderabad
yrd@cbit.ac.in

Abstract:

Clear-cut image segmentation of mammogram images is indispensable in malignant tumor detection. This paper is attempted to propose a nature-inspired optimized method for mammogram image segmentation by adopting Otsu's multi-level thresholding algorithm as a fitness function into the ABC algorithm. Moreover, in image segmentation, Multi-level thresholding algorithms come across with insufficient exploration and low exploitation on search space. Hence, to solve this problem a Metaheuristic optimized algorithm is leveraged. This is achieved by using the ABC algorithm to explore the population space and exploit the specified population space to select the finest threshold values. Thereafter, the output of ABC is used to segment the mammogram image using the multi thresholding method. In this work, the proposed method is exercised with a total of nine images from the MINI MIAS database. Besides, to assess the performance of the proposed method different threshold levels are used to segment mentioned images. It was witnessed that the performance of the wished-for method is effective and efficient to segment the mammogram images in terms of measures like PSNR, SSI, and computational time.

Keywords: Artificial bee colony, Otsu, Multi-level Thresholding, Mammogram, Breast cancer

1. Introduction

1.1 Medical Image Segmentation

Mammogram images are currently most widely adopted technique in clinical practice to detect the breast cancer as it is easily accessible and cost-effective. For early detection of malignant tumors in mammogram images, many methods have been proposed [12]. Breast cancer mainly affects middle-aged women for different reasons. Over the past twenty years, several methods are demonstrated to segment the medical images like X-ray, CT (computed tomography)-scan, Magnetic Resonance Imaging (MRI) Mammogram, etc. [1]. Homogeneous gray level values of pictorial muscle in preprocessed mammogram images exhibits effective intensity. Cancer detection false positive rate depends on the accuracy of image segmentation [16]. Image segmentation increases the visibility of microcalcification in processed mammogram images. In computer vision algorithms image segmentation plays a significant role [6]. There are six types of image segmentation methods, threshold-based, Artificial Neural Network (ANN) based, edge-based, clustering-based, watershed-based, region-based, and PDE-based methods[8]. Thresholding is the most popular segmentation method in medical image processing. In the bi thresholding method, the grayscale image is divided into two intensities i.e forefront and background. But, multi thresholding divides the images into many homogeneous regions [13].

1.2 Otsu's Multi Thresholding

In automatic global threshold case studies, gray level images can be effectively segmented into bimodal (foreground or background) or multi classes using a non-parametric and unsupervised Otsu's thresholding algorithm. It is centered on a very simple idea: exhaustively search for the threshold that reduces the weighted with in class variance defined as $\propto_w^2$ [22]. The class variances are given by (1) and (2) respectively

$$\propto_0^2 = \sum_{i=0}^{n} (i - \mu_0)^2 \Pr(i/C_0) = \sum_{i=0}^{n} (i - \mu_0)^2 p_i/w_0$$

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

$\propto_1^2 = \sum_{i=n+1}^{n} \quad (i - \mu_0)^2 \Pr(i/C_1) = \sum_{i=n+1}^{n} \quad (i - \mu_1)^2 p_i/w_1$

Let I represents a gray-level image that is segmented into two subclasses foreground (f) and background (g). using equation (1) and (2) intraclass variance is given by

$\propto_w^2 \ (t) = w_f(t) \propto_f^2 \ (t) + w_b(t) \propto_b^2 \ (t) \qquad (3)$

The Extension of Otsu bimodal to multi thresholding image segmentation is defined as $\propto_w^2 \ (n - thresholds)$ so it is required to find n thresholds that can segment images by minimizes the intraclass variance [3][10].

Let 'n' is the number of thresholds, then the image can be segmented into 'n+1' classes k_1,k2,...k_n [22].

Optimal thresholds k_1,k2,...k_n can be taken by maximizing the $\propto_w^2$ (4).

$$\propto_w^2 \ (k_1^*, k_2^* .. k_n^*) = \propto_w^2 \ (k1, k2 .. kn)$$

In this paper, the Otsu multi thresholding algorithm is used as an objective function. In bimodal Otsu assumes histograms and images are two classes, also stationary statics can be locally adaptive and uniform illumination. This method is comparatively fast once histogram is computed as it is applied directly on gray level image histograms (2D histogram).

1.3 Artificial Bee Colony

ABC is a "swarm intelligence-based meta-heuristic optimized" algorithm. Swarm-based processes are motivated by the collective behavior of distributed problem-solving capabilities of social insect colonies and social animal societies [21]. Exploration and exploitation are the two main functions of any metaheuristic-based algorithms. Self-organization and division of labor are the main properties of any swarm-based algorithms like ABC [2]. Honey bee colony contains three components, named as food sources, employed foragers, and unemployed foragers. Food sources can be represented with a property "profitability" based on their level of extraction, proximity, and food richness. Unemployed foragers are categorized into onlooker bees (OB) and scout bees (SB). Onlooker bees hunt for good sources based on waggle dances of employee bees (EB) and scout-bees hunt for next food sources near around [15].

ABC process is divided into three phases called EB, OB and SB phases. In the first phase, employed bees perform a greedy selection of a new solution and accept if it is healthier than the old solution in terms of the fitness function.

A new solution is generated with equation 4 for a randomly selected food source.

$X_{new}^j \ = X^j + \emptyset(X^j - X_P^j) \qquad (4)$

Where food source 'j' is selected randomly, $\emptyset$ is a random value between (-1, 1), and p is a randomly selected partner food source.

In the second phase, onlooker bees calculate the probability using equation (5) and repeat the same task done in the first phase.

$Prob_i = 0.9 * \frac{Fit_i}{\sum_1^n \ Fit} + 0.1 \qquad (5)$

Where 'Fit_i' objective function value of a particular solution. Unlike employee bees, one onlooker bee checks more than one food source for the best solution if the condition is not met whereas employee bee checks only one food source [20].

In the third phase, Scout bee abandoned the exhausted food source, if so, replaces the old solution with a new random solution X_k. X_k is generated by using Lowe bound(lb) and Upper bound (ub) .

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

X_k= lb+(ub-lb)*r (6)

In this paper, ABC uses the Otsu multi thresholding image segmentation method as an objective function. The population of Otsu objective function can be optimized by using exploration and exploitation properties of meta-heuristic algorithms.

The remaining paper is arranged in four sections, Section 2 contributes the recent research work done, the proposed method is described in section 3, section 4 discusses the results and analysis and section 5 presents the conclusion and future scope.

2. Literature Review

This section list out the research done in medical image processing, multi thresholding, and optimized algorithms in reverse chronological order.

[1] Mohamed Abd Elaziz et all [2021] proposed a meta-heuristic optimized image segmentation method called VPLWOA (Volleyball premier league using whale optimization algorithm), which is an alternate for image segmentation methods using multilevel thresholds. This method improves the VPL algorithm learning phase by using a local search system. Experimental results on datasets in terms of structural similarity index (SSR), peak signal noise

[4] Krishnaveni Arumugam et all [2020] proposed a Duck Traveler metaheuristic optimization algorithm to segment the breast images, it utilizes the IDTO calculation to amplify the threshold algorithms like Otsu's and Kapur's capacities. It is proved that it takes less time and leads to a high efficient methodology for a lower number of thresholds. Krishnaveni Arumugam et ell mentioned in the future it may be enhanced for a large number of thresholds also.

[6] Akmal Shafiq Badarul Azam, et all [2020] used the hybrid method for mammogram image microcalcification segmentation. "The method is combined by Canny Edge Detection, Otsu Thresholding, and 2D wavelet transform. The proposed method was measured in terms of accuracy, F-measure, and Error rate and produced 97.50%, 0.9280, and 0.1375 respectively".

[9] Ahmed A. Ewees et all [2020], presented a new hybrid metaheuristic method by combining the ABC and sine cosine (ABCSC) algorithm. In ABCSCA, Otsu's multilevel thresholding segmentation method is used as an objective function. This method is tested with various standard images in various levels of thresholding values. In this study, it is found that it can be applied in various medical image processing techniques like classification and clustering.

[14] Mourad Moussa et all [2020], created a system to segment the images for a better quality of boundaries. Mourad Moussa et all, used a nature-inspired metaheuristic optimized algorithm called ABC. Otsu's thresholding is used as an objective function in ABC. Experimental results on Berkeley, Oxford-17 Flowers, and Drive data sets are proved that this method takes less execution time.

[8] Krishna Gopal Dhal et all [2020], presented a study on all most important nature-inspired optimization algorithms (NIOA) to segment the images using multilevel thresholding. This paper shows how nature is inspiring researchers to solve recent and most complicated problems with the behavior of nature creation.

[17] Saban Ozturk et all [2020], presented a broad survey on the ABC algorithm in several levels of image processing, it includes classification, enhancement, clustering, and segmentation. In this research article, a total of 95 studies during the period 2010-2020 are examined. Out of 95 studies 42 are related to medical, out of 42 selected readings 15 are related to enhancement, 20 studies related to classification and 18 are linked to clustering and 42 academic studies are correlated to the segmentation method. This study finds many applications of the ABC algorithm in medical image processing.

[18] Kumar A. Santhos, et all [2020], employed three nature-motivated algorithms for mammogram segmentation. This study analyzed the Cuckoo Search optimization (CSO) algorithm, Electromagnetism

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

optimization, and Harmony search algorithm using PSNR, SSI, MSE, and Computation time. Experimental results on the MIAS dataset concluded that McCulloch's algorithm inspired by CSO (MACSO) with Otsu is segmenting images accurately.

[19] Zobia Suhail et all [2020], proposed a novel technique for mammogram segmentation based on histogram information to find mass areas. The presented algorithm is tested with 233 benign and 233 malignant abnormalities.

[11] Shubham Gupta et all [2019], proposed a hybrid SCAABC method for global optimization and gray image segmentation. In this paper, the sine cosine and artificial bee colony algorithm are combined by using the sine cosine equation to find the fitness value in employee bee 7/phase. This method improves the search strategy and also better convergence rate in various measures like performance index and convergence analysis.

[7] N.Bhaskar et all [2019], worked with the best frameworks executed in MATLAB to recognition of tumors in the lung by using FPCM and nature-inspired watershed algorithm. This method accomplished 99% precision in less than two seconds. The suggested technique can be related to other malicious growth types also.

[10] G.S. Gopika et all [2018], proposed an approach to segment the brain tumor images using a Fuzzy and artificial bee colony algorithm. This practice reduces the physical interaction and increases the classification ability.

[5] Mohammed A. Awadallah et all [2018], modifies the OB phase of ABC algorithm by evolutionary algorithms. THE modified OB phase is guided to search for the fittest food source from the population. In this study, 10 standard benchmark functions are tested to find the effectiveness of modification in the OB phase.

3. Proposed Methodology

There are seven steps (figure1) in methodology.

Step1: preprocessed Mammogram images

Step2: compute 2D histogram

Step3: Initialize ABC parameters

Step4: Perform Employee Bee phase (4) with Otsu

Step5: Perform onlooker Bee Phase (5) with Otsu

Step6: Perform Scout Bee phase (6)

Step7: segment the image if terminated

First, a preprocessed mammogram image is transformed to grayscale and will be given as input to this method. Second, compute the 2D histogram of mammogram grayscale image. Third, initializes parameters of ABC like dimensions, number of rows as the size of food sources, number of iterations as termination condition, lower bound and upper bound to corner bound the new solution, limits for scout bee phase (SBP), number of thresholds as the size of population and finally Otsu methods as an objective function to evaluate the fitness of food source. Fourth, the fitness of each food source is evaluated using an objective function in Employee Bee Phase (EBP), a food source and its partner is selected randomly for updating. If the new solution fitness is healthier than the old solution then EBP updates the population with the new one. Fifth, the onlooker bee phase (OBP) is the same as EBP with a probability associated with population updated previously. In OBP if a food source is not selected because of its bad fitness value then the next food source is considered. Whereas, in EBP, every food source is considered only once. Sixth, an exhausted food source is replaced with a randomly generated new solution using lower and upper bounds. A food source is treated as exhausted if its trial vector

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

value is more than the limit initialized. Seventh, segment the mammogram image by considering the updated population as optimized thresholds.

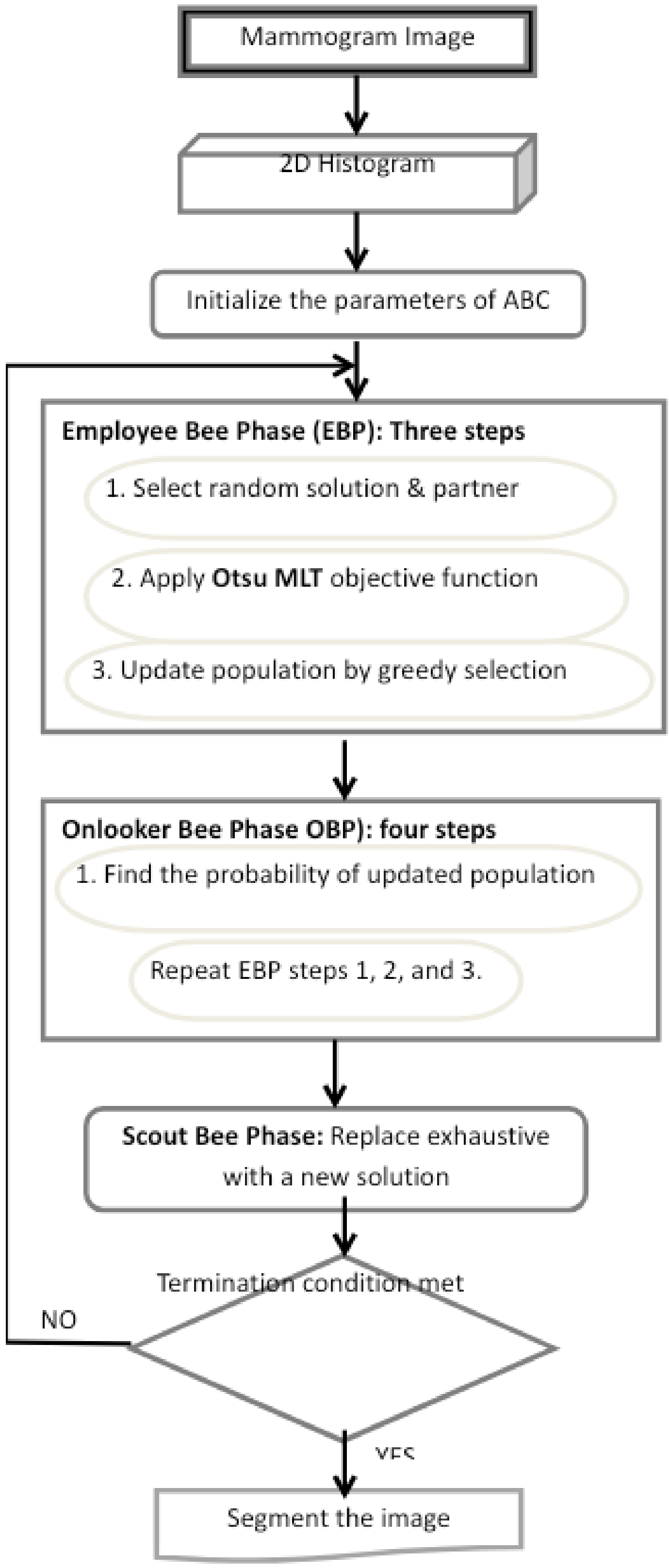


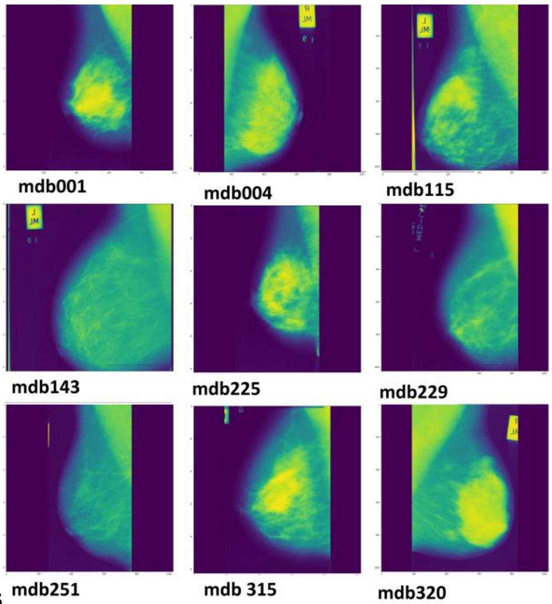
Figure 1: methodology

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

In the proposed method, the ABC meta-heuristic optimized algorithm is used to reduce the size of the population (exploration). Later, exploitation of metaheuristic algorithms is applied to find the best solution.

4. Results and Discussion

This section shows the experimental results of the proposed methodology on nine MINI MIAS database images. Experiments evaluation results are given in terms of various performance measures like PSNR, SSIM, and



Computational time. s

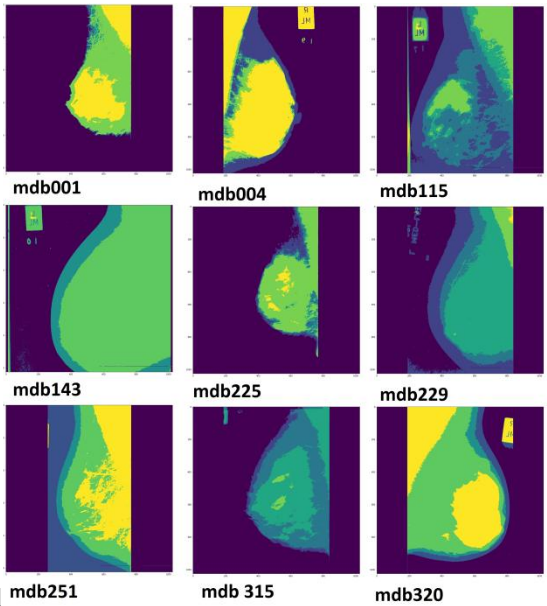


Figure 1: Original images in gray level

Figure 2: images after segmentation

Thresholds	Image	SSIM	PSNR	Time
3	mdb001	0.663737	32.49754	2.390625
	mdb004	0.537698	31.44865	2.1875
	mdb115	0.388624	30.20786	2.5
	mdb143	0.106236	29.2376	2.265625
	mdb225	0.624063	32.76796	2.25
	mdb229	0.554344	31.39582	2.28125

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

	mdb251	0.513175	31.75925	2.390625
	mdb315	0.501147	31.25206	2.34375
	mdb320	0.381098	29.61692	2.21875
	Average	**0.474458**	**31.13152**	**2.314236**
	mdb001	0.635033	32.39542	2.34375
	mdb004	0.542459	31.4384	2.5625
	mdb115	0.430201	30.30809	2.375
	mdb143	0.10559	29.21605	2.375
5	mdb225	0.617165	32.75491	2.328125
	mdb229	0.563601	31.36889	2.40625
	mdb251	0.523629	31.81639	2.359375
	mdb315	0.493634	31.20324	2.34375
	mdb320	0.384124	29.63815	2.375
	Average	**0.477271**	**31.12662**	**2.385417**
	mdb001	0.636424	32.41638	2.5625
	mdb004	0.531071	31.48424	2.578125
	mdb115	0.381511	30.23836	2.5625
	mdb143	0.091843	29.08205	2.546875
7	mdb225	0.614327	32.79582	2.53125
	mdb229	0.554788	31.41123	2.5625
	mdb251	0.523945	31.86892	2.609375
	mdb315	0.493946	31.21648	2.515625
	mdb320	0.374504	29.603	2.65625
	Average	**0.474458**	**31.13152**	**2.314236**

In this experiments, initially, all the necessary parameters are set as follows, several iterations are given as 10 which is a termination condition, limit is set to 1 to apply the scout bee phase if the trial vector value is exceeded the limit value, lower bound and upper bound is set to histogram-based values and size of the population is equal to the number of threshold values. The proposed method is evaluated in various threshold values like 3, 5, and 7. Table 1 list out the PSNR (peak signal-noise ratio), SSIM(structural similarity index), and Computational time value with thresholds 3, 5, and 7. Figure 2 shows the resulted images after applying the method with threshold values 3.

Table 1: average values of PSNR, SSIM, and Computational time for nine images with three different thresholds.

In table 1, the average values of all performance measures are recorded. Population with size five has given low average values compare to seven and three. Moreover, average values of threshold five and seven are identical for these nine images. Even though the number of threshold values and individual results are different, average measures are identical in both cases.

This section also compares the performance of the proposed methodology with Otsu and Multi Otsu without evolutionary algorithms in terms of PSNR SSIM and computational time. Table 2 gives the average values of PSNR, SSIM, and computational time of three methods. Moreover, multiOtsu and proposed methods are evaluated and compared with the same threshold values.

Image	**Otsu**	**Multi Otsu**	**ABCOTSU**
mdb001	0.763584	0.6340822	0.636424
mdb004	0.769975	0.5329125	0.531071
mdb115	0.70777	0.3879113	0.381511

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

mdb143	0.498496	0.096948	0.091843
mdb225	0.748896	0.6186737	0.614327
mdb229	0.782814	0.5541768	0.554788
mdb251	0.722552	0.5243431	0.523945
mdb315	0.721945	0.4929517	0.493946
mdb320	0.740343	0.3810938	0.374504
Average	0.717375	0.4692326	0.474458

Table 2: SSIM average values

Table 2 presents the average SSIM values of nine images with three different methods. it is observed that the proposed method outperforms the Multi otsu with a small margin.

Image	**Otsu**	**MultiOtsu**	**ABCOTSU**
mdb001	13.76563	32.41095	32.41638
mdb004	14.00551	31.40852	31.48424
mdb115	11.68125	30.20663	30.23836
mdb143	9.779062	29.1977	29.08205
mdb225	13.6273	32.81559	32.79582
mdb229	12.06233	31.36791	31.41123
mdb251	11.36012	31.83692	31.86892
mdb315	11.95873	31.20807	31.21648
mdb320	12.9833	29.63593	29.603
Average	12.35814	31.12091	31.13152

Table 3: PSNR average values

The proposed method outperforms the otsu method with a large margin and multi otsu with a small margin. PSNR is considered the most important property to evaluate the performance in image processing. The recorded values of nine images with the same threshold values are shown in table 3.

Image	**Otsu**	**Multi Otsu**	**ABCOTSU**
mdb001	6.90625	7	2.5625
mdb004	6.40625	9.0625	2.578125
mdb115	5.34375	8.265625	2.5625
mdb143	5.25	7.1875	2.546875
mdb225	5.328125	4.859375	2.53125
mdb229	6.953125	8.375	2.5625
mdb251	6.453125	7.71875	2.609375
mdb315	5.65625	7.234375	2.515625
mdb320	5.45	8.546875	2.65625
Average	5.971875	7.5833333	**0.583747**

Table 4: Average Computational time

Table 4 presents the average computational time. It is observed that the proposed method takes less time to compare with the two other methods. it is concluded from table 2, table 3, and table 4 that the proposed method is better than the comparative methods.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 12353 - 12362
Received 05 March 2021; Accepted 01 April 2021.

5.Conclusion

In this paper, a meta-heuristic optimized ABC algorithm is used to maximize the Otsu objective function in mammogram image segmentation. Otsu's multi-level thresholding algorithm is given as a fitness function to find optimized threshold values and thereafter segment the images efficiently. Hence, the proposed method performs experiments on a total of nine images at different threshold levels. Moreover, bi-level Otsu, Multilevel Otsu, and multi-level Otsu with ABC are performed on eight images separately. Performance metrics like Peak-Signal-Noise-Ratio (PSNR) and Structural Similarity Index (SSI) and Computational time are used to analyze the results of four methods. Based on mammogram image results, it is observed that ABC with Otsu multi-level thresholding algorithm as fitness function outperform the bi-level Otsu and multi-level Otsu. In the Future, ABC can adopt other multi-level thresholding algorithms like Kapur's entropy as a fitness function. Furthermore, ABC becomes more emphasized for other image processing techniques like classification clustering.

References

[1] M. Abd Elaziz, N. Nabil, R. Moghdani, A. A. Ewees, E. Cuevas, and S. Lu, *Multilevel thresholding image segmentation based on improved volleyball premier league algorithm using a whale optimization algorithm*. Multimedia Tools and Applications, 2021.

[2] B. Alatas, "Chaotic bee colony algorithms for global numerical optimization," *Expert Syst. Appl.*, vol. 37, no. 8, pp. 5682–5687, 2010, doi: 10.1016/j.eswa.2010.02.042.

[3] S. Arora, J. Acharya, A. Verma, and P. K. Panigrahi, “Multilevel thresholding for image segmentation through a fast statistical recursive algorithm,” *Pattern Recognit. Lett.*, vol. 29, no. 2, pp. 119–125, 2008, doi: 10.1016/j.patrec.2007.09.005.

[4] K. Arumugam, S. Ramasamy, D. Subramani, and A. Professors, “IMPROVED DUCK AND TRAVELER OPTIMIZATION (IDTO) ALGORITHM : A TWO- WAY EFFICIENT APPROACH FOR BREAST TUMOR SEGMENTATION USING MULTILEVEL THRESHOLDING,” vol. 7, no. 10, pp. 3793–3808, 2020.

[5] M. A. Awadallah, M. A. Al-Betar, A. L. Bolaji, E. M. Alsukhni, and H. Al-Zoubi, “Natural selection methods for artificial bee colony with new versions of onlooker bee,” *Soft Comput.*, vol. 23, no. 15, pp. 6455–6494, 2019, doi: 10.1007/s00500-018-3299-2.

[6] A. S. B. Azam, A. A. Malek, A. S. Ramlee, N. D. S. M. Suhaimi, and N. Mohamed, “Segmentation of Breast Microcalcification Using Hybrid Method of Canny Algorithm with Otsu Thresholding and 2D Wavelet Transform,” *Proc. - 10th IEEE Int. Conf. Control Syst. Comput. Eng. ICCSCE 2020*, no. August, pp. 91–96, 2020, doi: 10.1109/ICCSCE50387.2020.9204950.

[7] N. Bhaskar and T. S. Ganashree, *Lung Cancer Detection with FPCM and Watershed Segmentation Algorithms*, vol. 3. Springer International Publishing, 2020.

[8] K. G. Dhal, A. Das, S. Ray, J. Gálvez, and S. Das, *Nature-Inspired Optimization Algorithms and Their Application in Multi-Thresholding Image Segmentation*, vol. 27, no. 3. Springer Netherlands, 2020.

[9] A. A. Ewees, M. Abd Elaziz, M. A. A. Al-Qaness, H. A. Khalil, and S. Kim, “Improved Artificial Bee Colony Using Sine-Cosine Algorithm for Multi-Level Thresholding Image Segmentation,” *IEEE Access*, vol. 8, pp. 26304–26315, 2020, doi: 10.1109/ACCESS.2020.2971249.

[10] G. S. Gopika, J. Shanthini, and S. Karthik, “Hybrid Approach for the Brain Tumors Detection & Segmentation Using Artificial Bee Colony Optimization with FCM,” *ICSNS 2018 - Proc. IEEE Int. Conf. Soft-Computing Netw. Secure.*, pp. 1–5, 2018, doi: 10.1109/ICSNS.2018.8573648.

[11] S. Gupta and K. Deep, “Hybrid sine cosine artificial bee colony algorithm for global optimization and image segmentation,” *Neural Comput. Appl.*, vol. 32, no. 13, pp. 9521–9543, 2020, doi: 10.1007/s00521-019-04465-6.

[12] S. M., A. A., H. E., and M. T., “Breast Cancer Detection with Mammogram Segmentation: A Qualitative Study,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 10, pp. 117–120, 2017, doi: 10.14569/ijacsa.2017.081016.

[13] A. Mostafa *et al.*, "CT liver segmentation using artificial bee colony optimization," *Procedia Comput. Sci.*, vol. 60, no. 1, pp. 1622–1630, 2015, doi: 10.1016/j.procs.2015.08.272.

[14] M. Moussa, W. Guedri, and A. Douik, “A novel metaheuristic algorithm for edge detection based on artificial bee colony technique,” *Trait. du Signal*, vol. 37, no. 3, pp. 405–412, 2020, doi: 10.18280/ts.370307.

[15] T. H. Muliawati, C. Fatichah, D. Herumurti, K. Uchimura, and G. Koutaki, “Image Segmentation Using Multi-level Artificial Bee Colony Algorithm.”

[16] A. M. Omer and M. Elfadil, “Preprocessing of Digital Mammogram Image Based on Otsu ’ s Threshold,” *Am. Sci. Res. J. Eng. Technol. Sci.*, vol. 37, no. 1, pp. 220–229, 2017.

[17] Ş. Öztürk, R. Ahmad, and N. Akhtar, “Variants of Artificial Bee Colony algorithm and its applications in medical image processing,” *Appl. Soft Comput. J.*, vol. 97, 2020, doi: 10.1016/j.asoc.2020.106799.

[18] K. A. Santhos, A. Kumar, V. Bajaj, and G. K. Singh, “McCulloch’s algorithm inspired cuckoo search optimizer based mammographic image segmentation,” *Multimed. Tools Appl.*, vol. 79, no. 41–42, pp. 30453–30488, 2020, doi: 10.1007/s11042-020-09310-w.

[19] Z. Suhail and R. Zwiggelaar, “Histogram-based approach for mass segmentation in mammograms,” no. May, p. 34, 2020, doi: 10.1117/12.2563621.

[20] S. Zhang, W. Jiang, and S. Satoh, “Multilevel thresholding color image segmentation using a modified artificial bee colony algorithm,” *IEICE Trans. Inf. Syst.*, vol. E101D, no. 8, pp. 2064–2071, 2018, doi: 10.1587/transinf.2017EDP7183.

[21] D. Karaboga and C. Ozturk, “A novel clustering approach: Artificial Bee Colony (ABC) algorithm,” *Appl. Soft Comput. J.*, vol. 11, no. 1, pp. 652–657, 2011, doi: 10.1016/j.asoc.2009.12.025.

[22] Nobuyuki Otsu, “A Threshold Selection Method from Gray-Level Histograms,” *IEEE Trans. Syst. Man Cybern*, vol. 9, no. 1, pp. 62–66, 1979.

[23] D. R. S. . et. al., “ESTIMATING THE EFFICIENCY OF MACHINE LEARNING IN FORECASTING HARVESTING TIME OF RICE”, IJMA, vol. 10, no. 2, pp. 1930 - 1937, Apr. 2021.