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SEGMENTATION OF THYROID IMAGES USING BACKTRACKING SEARCH ALGORITHM

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Abstract— Thyroid cancer is one of the fastest growing cancer diagnoses worldwide. Thyroid cancer commences from a typical growth of thyroid tissue at the edge of the thyroid gland. Thyroid image segmentation is one of the major steps in image analysis that subdivides an image into various constituent parts. The majority of image segmentation methods are based on thresholds obtained from image histogram. The difficulty in subdividing the image based on histogram is finding optimal threshold. Due to the complexity associated with histogram of thyroid medical images, the classical segmentation methods finds it difficult to obtain optimal threshold, thus either Swarm Algorithm (SA) or Evolutionary Algorithms (EA) are chosen to be an alternatives. The Backtracking Search Algorithm (BSA) is a newly introduced EA algorithm. The BSA has been proved to be very successful on various standard benchmark optimization problems and has one tuning parameter called amplitude control factor. This factor decides about generating trial population in BSA algorithm. Though there is only one control parameter, the trial population may be generated by various means centered on random strategy. This research paper develops various BSA variants based on trial population generation strategies and used for thyroid image segmentation. The comprehensive analysis of BSA variants is presented on multi-level image thresholding. It is found that BSA variants shows almost comparable solution and proves the robustness of BSA algorithm.

Keywords — Evolutionary Algorithms, Image Segmentation, Optimal thresholds, Swarm Algorithm, Thresholding, Thyroid Nodule, Variants.

1 INTRODUCTION

Image segmentation is a process of dividing an image into various subcomponents and it plays an important role in image analysis. Among many image segmentation methods, histogram based thresholding is more popular [1]. A threshold divides the image into sub-images. Further an image may efficiently be segmented using multilevel

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thresholding, where multiple thresholds need be provided in advance. The decision of deciding thresholds in advance is a challenge. The optimal thresholds may be found by optimizing an objective function built around histogram information of an image [2]. A segmentation technique must retain the full size and shape of the anomaly while completely removing the unwanted regions. In discontinuity-based segmentation, edges, points and lines of the hotspot are detected and morphological image processing technique is then applied for detecting the hotspot. The shape and size of the structuring elements chosen for morphological image processing is dependent on the hotspot size and shape and cannot be standardized. Similarity between the pixels namely intensity, brightness, contrast etc results in heuristic choice of threshold, which is a major limitation of similarity based segmentation techniques [3].

The BSA algorithm shares many similarities with other EA algorithms [3]. It is different from the other EAs, as it has only one controlling parameter called amplitude control factor. The value and range of this parameter balances between exploration and exploitation of search process. Though there is only one parameter to be tuned, but there is a possibility of developing BSA variants based on this parameter to generate trial population having different generation strategies [4]. The trial population is generated using various random number generating strategies and hence the BSA variants. These variants are applied for image segmentation for comprehensive performance analysis. One of the recently introduced EA algorithms is the Backtracking Search Algorithm (BSA) developed in 2013 by Pinar Civicioglu [5].

2 PROPOSED Methodology

2.1 Backtracking Search Algorithm variants

The BSA has only one control parameter and has less chance of tuning and getting new variants. The heart of BSA algorithm is the mutation strategy. The mutation strategy of BSA algorithm generates intermittent population for further search process. It follows the equation,

mutant = X + F * (Xold - X)

Where X is the current population individual, Xold is previous population individual and F is amplitude control parameter. The value of F used in [6] is 3*rndn, where rndn is random number generator based on standard normal distribution. Though there is only one tuning parameter in BSA algorithm, it gives a room for changing amplitude control parameter based on various random strategies; hence following BSA variants are obtained.

Execution flow of BSA algorithm

Step 1: Initialize population and other parameters

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Step 2: while t ≤ MaximumIteration do

Step 3: Selection-I

Step 4: Trial population generation

Step 5: Mutation

Step 6: Crossover

Step 7: Selection-II

Step 8: t=t+1

Step 9: end while

BSA1

This variant is obtained by changing amplitude control parameter F by a random strategy based on standard Brownianwalk. The scale factor used in this variant is F = 3 * randn, where randn is based on normally distributed pseudorandom number generator [6].

BSA2

This variant is developed using scale factor F, which is based on normal brownian-walk, where F = 4 * randg. These random values are chosen from a gamma distribution with unit scale and shape for trial population generation.

BSA3

This variant uses F = lognrnd(rand, 5 * rand) that follows brownian-walk. The random numbers generated from the lognormal distribution with parameters MU and SIGMA. The MU and SIGMA are the mean and standard deviation, respectively, of the associated normal distribution.

BSA4

Here F is initialized as F = 1/normrnd(0,5) and follows levy-like pseudo-stable walk. The random numbers chosen from a normal distribution with mean MU = 0 and standard deviation SIGMA = 5.

BSA5

This variant follows levy-like pseudo-stable walk that and has inverse gamma distribution, F = 1/gamrnd(1,0.5). The random numbers chosen from the gamma distribution with shape parameter A = 1.0 and scale parameter B = 0.5.

BSA6

This variant follows normal / Gaussian distribution for random number generator. Here F = rand, the rand generates pseudorandom values drawn from the standard uniform

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distribution on the open interval (0,1).

2.2 Image Segmentation

Image segmentation divides or segregates an image into different non-overlapping parts or regions. It plays an important role in image analysis and is treated to be difficult area [7]. Since it is difficult for a computer or image analysis hardware to separate important regions in an image, hence built-in intelligence for efficient division is of prime importance [8]. The image segmentation may be based on various characteristics found in an image like color or pixel information [9]. One of the most common method of segmentation is the thresholding method, which is commonly used for segmentation of an image into two or more clusters [10]. Image segmentation is the problem of partitioning an image into meaningful parts, and among many segmentation methods, thresholding is more popular. The problem in multilevel threshold is, requirement of optimum thresholds in advance. The optimum thresholds are selected by optimizing an objective function built by using histogram of an image. Since in most of the cases, histogram of the images has multiple peaks, hence the classical segmentation method often fails to give good results. There are many Swarm and Evolutionary algorithms that have shown promising results on multimodal benchmark optimization problems, hence are the alternative to multilevel image threshold segmentation.

Multilevel threshold segmentation

Multilevel thresholding [11] provides multiple thresholds in advance for segmentation and is an efficient way to perform image analysis. The n-level threshold problem can be converted to an optimization problem as given in the following equation,

$$\mathrm{TC} = [\mathrm{RBG}] = \sum_{j=1}^{n} w^{cj}\ (\mu\ cj - \mu\ cj)^2$$

Where j represents a specific class. The Wcj is the probability of occurrence and µcj is the mean of class j, these will be calculated in a standard way for L intensity levels and n - 1 threshold levels [12].

3 RESULTS AND DISCUSSIONS

The simulations were carried out on a computer having intel Corei5 processor with 8GB of RAM. The BSA variants were written using MatlabR2013a on a Windows-10.1 platform. The standard test images which have multimodal histogram are used for performance comparison, like thyroid nodule image 1 and thyroid nodule image 2. All the BSA variants are initialized with a population size of 30. Each BSA variant is

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executed 30 times and each time they are run for 1000 iterations.

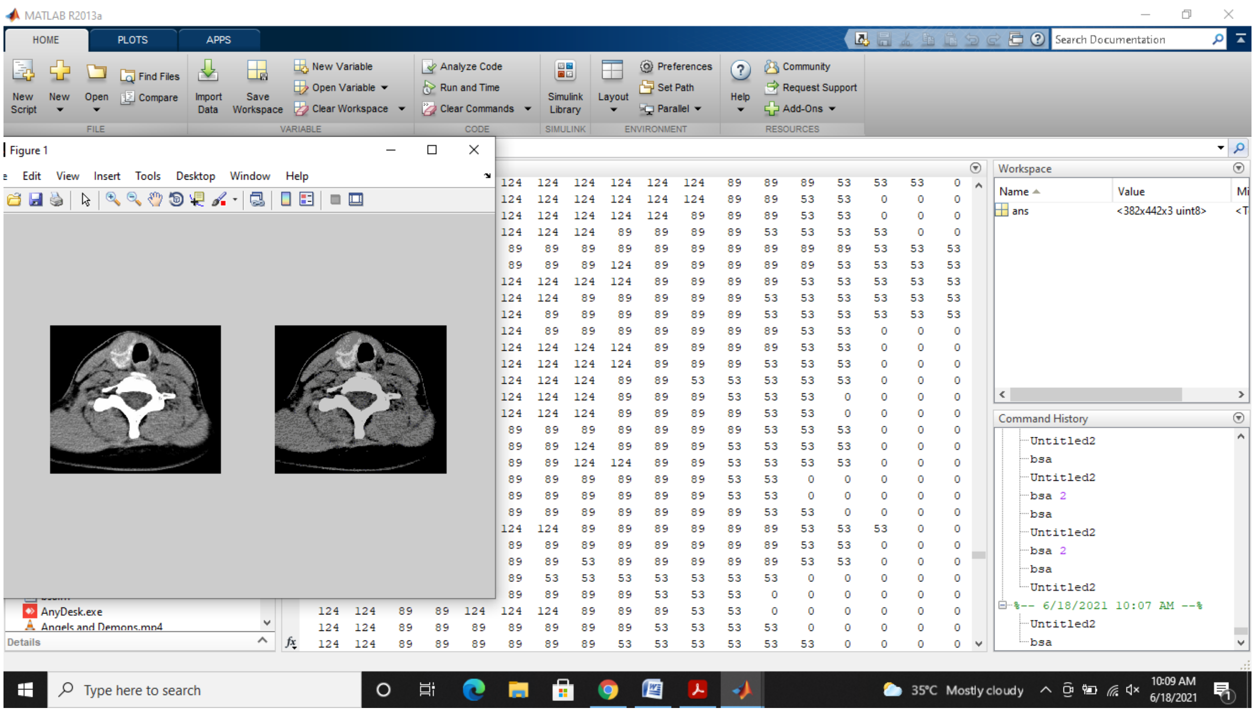

Fig. 1. Segmented image of thyroid by BSA1 with 2 threshold

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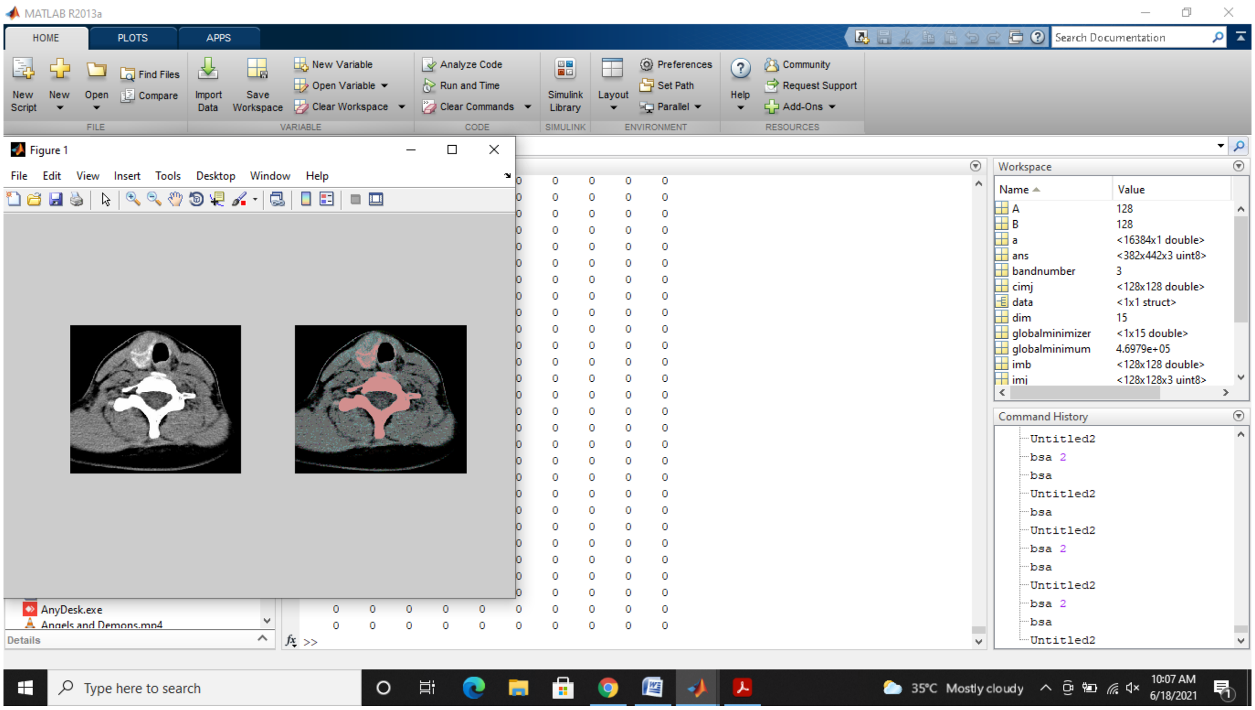


Fig. 2. Segmented image of thyroid by BSA2 with 2 threshold

Table 1. Average fitness results obtained on different images for various thresholds

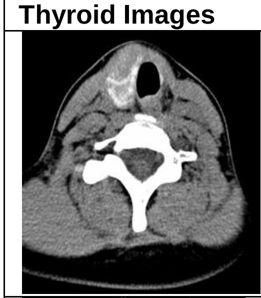
Thyroid Images	Thr	BSA1	BSA2	BSA3	BSA4	BSA5	BSA6
	1	18.10251	18.10254	18.10254	18.10251	18.10251	**18.10206**
	2	**19.67244**	19.67343	19.67454	19.67356	19.67373	19.67452
	3	20.41985	20.42112	20.42713	20.42978	20.42511	**20.40993**
	4	20.83742	20.84645	20.83954	20.85560	20.84959	**20.83699**
	1	12.38082	12.38082	12.38082	12.38082	12.38082	**12.38028**
	2	15.65753	15.65821	15.65783	15.65774	15.65821	**15.65591**
	3	16.55942	16.56182	16.56375	**16.55387**	16.55878	16.56585
	4	**17.08242**	17.08940	17.08766	17.08640	17.09207	17.08598

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Table II. PSNR results obtained for different images and thresholds

Thyroid Images	Thr	BSA1	BSA2	BSA3	BSA4	BSA5	BSA6
	1	11.40337	11.37916	11.37916	11.40337	11.40337	**11.47916**
	2	**15.49319**	14.85663	15.00411	14.86245	14.92658	14.93333
	3	18.34021	18.68288	18.55534	18.47124	18.59757	**18.91915**
	4	20.35043	20.67158	20.56172	20.44691	20.16411	**20.76466**
	1	10.72082	10.72082	10.72082	10.72082	10.72082	**10.72088**
	2	15.34763	15.34763	15.34763	15.34648	15.34763	**15.37293**
	3	17.42268	17.34402	17.43758	**17.50473**	17.39485	17.43066
	4	**20.1288**	19.82042	19.70224	19.95248	20.18105	19.99234

Table III. Optimal thresholds obtained by BSA variants

Thyroid Images	BSA1	BSA2	BSA3	BSA4	BSA5	BSA6
	153	153	153	153	153	153
	113, 174	114, 174	112, 173	114, 174	112, 173	112, 173
	92, 144,190	92,143,190	92,144,190	93,145,190	92,144,189	91,143,191
	81,127,168, 200	69,118, 63, 198	69,117,161, 197	80,126,171, 201	70,118,163, 199	62,112,159, 196
	129	129	129	129	129	129
	97, 149	97, 149	97, 149	97, 149	97, 149	98,150
	84,124, 161	85,124,160	85,125, 161	85,125, 162	84,124,160	85,125, 161
	71,106,137, 167	71,106,136, 167	71,106,135, 166	70,105,136, 166	72,107,137, 168	71,104,134, 166

The Table I to Table III presents the results in numerical form. The Table I present average fitness results. It can be seen from Table I that, the BSA6 does well on thyroid image 1 with threshold 1, 3 and 4, similarly BSA1 does well on threshold 2. On thyroid image 2, the BSA6 shows good results with threshold 1 and 2. The BSA1 and BSA4 shows good result with threshold 4 and 3 respectively. From Table I, it is seen that, though the individual BSA variants shows little different results, but they perform equally well on almost all the test images. With close inspection of results from Table I, it may be found that, as number of threshold increases from 1 to 4, the complexity of the objective function increases and performance of the variants decreases.

The Table II presents the average Peak Signal to Noise Ratio (PSNR) for various thresholds. The more the PSNR value better is the performance. This table shows the similar trend by all the variants as is seen from Table I. The table depicts equal performance of all the variants. The Table III presents optimal thresholds obtained by various BSA variants. This table agrees with most of the notable work in the segmentation domain.

4 CONCLUSION

This paper presents the performance analysis of Backtracking Search Algorithm (BSA) variants for efficient segmentation of images. The amplitude control factor of BSA algorithm decides about generating trial population in search process. This factor is changed using various random strategies to obtain variants of BSA and hence six BSA variants are proposed in this paper. Further the comprehensive performance analysis of BSA variants for determining optimal thresholds in image segmentation is presented. Simulation results show that BSA variant that follows Gaussian random strategy for generating trial population shows promising performance compared to other proposed variants. The close inspection on simulation results conclude that, all the variants shows equal and comparable performance on almost all the situation. This proves the robustness of BSA algorithm on image segmentation also.

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