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Research Article

Solution of Multilevel Image Thresholding Using Rao Algorithms

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Abstract

With a rapid expansion of image segmentation over the decades, the growth of the mathematical optimization in the form of image thresholding is enormous on the segmentation. A need to organize the image thresholding arises to help medi-cal imaging, detection, and recognition in making an informed decision about the image. The proposed Rao algorithms are relied upon to quickly get the top-notch optimal thresholds are controlled by maximizing the Kapur entropy of various classes. Different from previous optimization techniques, Rao algorithms have been utilized as a prime optimization method as it has been ended up being a successful optimization when applied to different down to earth optimization issues and its execution is straightforward including less computational exertion. The technique has been tried on standard benchmark test images and the examination of the numerical outcome shows that this method is a promising option for the multilevel image thresholding issue

Keywords: Kapur's Entropy, Multilevel Thresholding, Rao Algorithms

1. Introduction

Thresholding is a strategy broadly utilized in image partition. The goal of thresholding is to decide a threshold value to segment the image space into important areas. Thresholding is an important advance in many image processing, for example, identification of machine-printed or written by hand messages, identification of item shapes, and image enhancement. The primary reason for image thresholding is to decide one (bi-level thresholding) or k (multilevel thresholding) fitting thresholds for an image to isolate pixels of the image into various regions [1]. In the ongoing years, expanding unpredictability of computerized images, for example, force inhomogeneity, makes multilevel thresholding (MT) approaches drawn significantly more consideration. This is for the most part because of its simple execution and low stockpiling memory trademark [2].

The MT changes the image thresholding to an optimization issue where the fitting thresholds are found by expanding or limiting a measure. The prominent Otsu's technique [3], thresholds are controlled by amplifying the between-class variance. In Kapur's entropy [4], the ideal thresholds are accomplished by expanding the entropy of various classes. Specialists have likewise built up some other ideal criteria, including Tsallis entropy [5], Renyi's entropy [6], etc.

Among these methodologies, Kapur technique picks the best threshold worth by maximizing the entropy of various classes, has pulled in critical consideration from established researchers. In any case, this technique has a conspicuous downside in that the computational multifaceted nature increments exponentially with an expansion in the number of required thresholds. Partially, this restricts its application in MT, various methodologies and comparing upgrades have been proposed to wipe out the previously mentioned downsides.

Grey wolf optimizer (GWO) is propelled from the social and chasing conduct of the grey wolves. This metaheuristic is applied to MT issues utilizing Kapur entropy function. The exhibitions of the proposed technique are then contrasted and improved adaptations of PSO and bacterial foraging optimization based MT strategies [7]. To maximize Kapur's objective function, symbiotic organisms search (SOS) is utilized. The standard images are pre-tried and contrasted with particle swarm optimization (PSO), firefly algorithm (FA), artificial bee colony (ABC), genetic algorithm (GA), GWO [8].

The proposed Rao algorithms is a technique explicit, the parameterless calculation that doesn't require any method explicit parameters to be tuned for image segmentation dependent on Kapur's technique. During the refreshing procedure, the nature of every result is assessed utilizing the Kapur entropy function. As showed by the objective function, the consequence of results is invigorated subject to the qualities of the Rao algorithms until an end basis is fulfilled. The consequences of the Rao algorithms calculation have been contrasted and other metaheuristic calculations. The exhibition of the distinctive method has been evaluated on standard benchmark test pictures utilizing the best fitness values and Jaccard measure.

The remainder of this paper is formed as follows: In Section 2, the issue plan and the meaning of Kapur's strategy are presented. The proposed techniques for MT dependent on the Rao algorithms are represented in Section 3. The analyses and results are given in Section 4. At last, the conclusion and future work are recorded in the last section.

2. MT Criterion Based on Kapur Method

The thresholding procedure performs image thresholding dependent on the data contained in the picture histogram. This is performed by maximizing an objective function that utilizes the chose thresholds as the parameters. Right now, the thresholding strategy to be specific entropy of the segmented classes (Kapur) technique is utilized. Thresholding utilizing Kapur technique is a nonparametric thresholding method, which is utilized to partition the whole picture into numerous regions; in this way, the entropy and statistical distribution of the picture histogram can be maximized. Since Kapur technique is an entrenched basis, the detailed conversation on Kapur technique isn't introduced here. Perusers can allude [4, 7, 8] for additional subtleties.

3. The Proposed Algorithm for MT

3.1 Rao Algorithms

Rao algorithms (three algorithms) are a global optimization technique initially created by Rao [9]. Rao algorithms are a population-based optimization method in which a gathering of results is executed to arrive at an optimum solution. These three algorithms consistently attempt to draw nearer to progress (for example arriving at the best solution) and attempts to keep away from regress (for example moving ceaselessly from the most noticeably worst solution) and the random interactions between the candidate solutions. The proposed algorithms [9] are named Rao-1, Rao-2, and Rao3 and it is relatively simpler to apply. The result designations are haphazardly conveyed all through the search space. In this manner, among the results, the best solution is chosen.

3.2 Mathematical Model of Rao Algorithms

Let f(x) is the Kapur's' fitness function to be maximized. At any cycle *i*, expect that there are 'm' be the number of thresholds (for example *j*=1, 2, 3, 4, 5), 'n' be the number of possible solutions (for example population size, *k*=50). Let the best possible best get the best estimation of f(x) (for example $f(x)_{best}$) in the whole possible solutions and the most exceedingly worst estimation of f(x) (for example $f(x)_{worst}$) in the whole possible solutions [10]. On the off chance that $X_{j,k,l}$ is the estimation of the *j*th variable for the *k*th solution during the *i*th cycle, at that point this value is changed according to the accompanying (1).

$$\begin{aligned} X'_{j,k,i} &= X_{j,k,i} + r_{1,j,i} (X_{j,best,i} - X_{j,worst,i}) \end{aligned}$$
(1)

$$\begin{aligned} X'_{j,k,i} &= X_{j,k,i} + r_{1,j,i} (X_{j,best,i} - X_{j,worst,i}) + r_{2,j,i} (|X_{j,k,i} \text{ or } X_{j,l,i}| - |X_{j,l,i} \text{ or } X_{j,k,i}|) \end{aligned}$$
(2)

$$\begin{aligned} X'_{j,k,i} &= X_{j,k,i} + r_{1,j,i} (X_{j,best,i} - |X_{j,worst,i}|) + r_{2,j,i} (|X_{j,k,i} \text{ or } X_{j,l,i}| - (X_{j,l,i} \text{ or } X_{j,k,i})) \end{aligned}$$
(3)

where, $X_{j,best,i}$ is the estimation of the variable *j* for the best solution and $X_{j,worst,i}$ is the estimation of the variable *j* for the most noticeably worst solution. $X'_{j,k,i}$ is the updated estimation of $X_{j,k,i}$ and $r_{1,j,i}$ and $r_{2,j,i}$ are the two random numbers for the *j*th variable during the *i*th cycle in the range [0, 1]. In (2) and (3), the term $X_{j,k,i}$ or $X_{j,l,i}$ shows the candidate solution *k* is compared with any randomly picked candidate solution *l* and the information is exchanged based on their fitness values [11].

These three algorithms consistently attempt to draw nearer to the best solution and attempts to keep away from the worst solution and the random interactions between the candidate solutions. The (1), (2), and (3) are used in the Rao1, Rao2, and Rao3 algorithms respectively. Researchers can refer to [9-11] for more details.

3.3 Implementation Procedure of Rao Algorithms

The methods connected with the execution of the algorithm for dealing with MT issue are as per the following:

1. Read the standard benchmark test image and instate Rao algorithms parameters, for example, population size and the most extreme number of generations.

2. Identify the best and worst optimal threshold values without violating constraints.

3. Applying changes to the solutions based on the best and worst solution in (1) for Rao1, (2) for Rao2, and (3) for Rao3 algorithms.

4. Compare fitness values and hold the best; if the solution corresponding to $X'_{j,k,i}$ better than that corresponding to $X_{j,k,i}$ otherwise keep the previous solution.

5. Go to Step 2 if the program's end conditions are not fulfilled.

4. Experiments and Results

4.1 Benchmark Images

The six standard benchmark test pictures are generally used images: Cameraman, Peppers, Ostrich, Flower, Plane, and Girl, as appeared in Fig. 1, individually. Size of each tried benchmark pictures is 256×256, 256×256, 321×481, 481×321, 481×321, and 321×481 pixels with 8-bit gray-levels, respectively.



(a) Cameraman







(c) Ostrich



Fig.1. The standard benchmark test images: Cameraman, Peppers, Ostrich, Flower, Plane, and Girl.

4.2 Experimental Settings

In this section, tests are done on benchmark gray-scale pictures, Cameraman, Peppers, Ostrich, Flower, Plane, and Girl (refer to Fig. 1), and the Jaccard metric [12] are utilized to look at image thresholding execution. The application and execution of the Rao algorithms for taking care of MT issues have been uncovered by

actualizing on standard benchmark test images. The parameters picked to obtain the optimal threshold values are population size = 50 and most number of generations = 100.



Fig.2. Segmented images with thresholds levels k = 1, 2, 3, 4, and 5 obtained by the Rao1 algorithm.

4.3 Segmented Image Quality Metrics

To judge the quality of the algorithm to choose multi-thresholds, the Jaccard measure is utilized. It is an amount of similarity for the two sets of pictures, with a range from 0 to 1. The best algorithm is the one that has a higher estimation of Jac.

$$Jac = \frac{|I_{original} \cap J_{segmentedimage}|}{|I_{original} \cup J_{segmentedimage}|}$$
(4)

Table 1.Optimal threshold and Jaccard measures gained by the Rao algorithms.

k	Rao1 Thresholds	Јас	Rao2 Thresholds	Јас	Rao3 Thresholds	Jac
1	193	0.02	193	0.02	193	0.02
2	128, 193	0.60	128, 193	0.60	128, 196	0.60
3	44, 101, 193	0.78	44, 104, 193	0.78	44, 104, 196	0.78
4	44, 97, 146, 197	0.78	44, 97, 146, 197	0.78	44, 97, 146, 197	0.78
5	25, 62, 100, 146, 196	0.80	24, 61, 100, 146, 197	0.81	24, 60, 98, 146, 197	0.81
1	80	0.78	80	0.78	80	0.78
2	74, 147	0.81	74, 147	0.81	74, 147	0.81
3	58, 111, 165	0.86	58, 111, 165	0.86	58, 111, 165	0.86
4	56, 104, 148, 195	0.87	43, 79, 125, 171	0.90	43, 79, 125, 171	0.90
5	41, 77, 114, 154, 195	0.91	41, 77, 114, 154, 195	0.91	42, 78, 114, 154, 195	0.90
1	127	0.08	127	0.08	127	0.08
2	119, 180	0.10	119, 180	0.10	119, 180	0.10
3	75, 123, 183	0.53	75, 123, 183	0.53	117, 159, 201	0.10
4	30, 77, 123, 175	0.99	74, 119, 159, 201	0.54	74, 119, 159, 201	0.54

Solution of N	Multilevel l	mage '	Thresholding	Using	Rao A	lgorithms
				0		0

k	Rao1 Thresholds	Јас	Rao2 Thresholds	Јас	Rao3 Thresholds	Jac
5	30, 75, 119, 159, 201	0.99	30, 75, 119, 159, 201	0.99	30, 75, 119, 159, 201	0.99
1	137	0.10	137	0.10	137	0.10
2	118, 181	0.16	118, 181	0.16	118, 181	0.16
3	78, 130, 188	0.51	78, 130, 188	0.51	78, 130, 188	0.51
4	73, 118, 160, 209	0.56	73, 118, 161, 208	0.56	73, 118, 161, 208	0.56
5	70, 111, 147, 182,	0.59	70, 111, 147, 182,	0.59	71, 113, 149, 185,	0.58
	218		219		220	
1	84	0.93	84	0.93	84	0.93
2	66, 101	0.95	66, 101	0.95	66, 101	0.95
3	35, 72, 102	0.96	35, 72, 102	0.96	35, 72, 102	0.96
4	35, 71, 102, 158	0.96	35, 72, 102, 158	0.96	35, 72, 102, 158	0.96
5	34, 66, 96, 121, 158	0.96	34, 66, 96, 121, 158	0.96	35, 69, 97, 121, 159	0.96
1	109	0.78	109	0.78	109	0.78
2	106, 202	0.80	106, 202	0.80	106, 202	0.80
3	94, 143, 202	0.85	94, 143, 202	0.85	95, 144, 204	0.85
4	36, 84, 139, 202	0.91	36, 84, 139, 202	0.91	37, 84, 139, 202	0.91
5	36, 84, 134, 178, 211	0.91	36, 84, 134, 178, 211	0.91	36, 84, 134, 178, 211	0.91

4.4 The Results and Discussions

Since the Rao algorithms are stochastic, it is important to utilize a proper statistical measurement to quantify its efficiency. So as to keep up similarity with comparable works detailed in the writing [8], the number of thresholds focuses utilized in the test are k = 1, 2, 3, 4, and 5. The enhanced visualizations of Fig. 1 at different threshold levels k = 1, 2, 3, 4, and 5 are shown in Fig. 2 which shows that the nature of the segmented image comes about because of applying the Rao1 algorithm.

From Table 1, the optimal thresholds together with the Jaccard measures are computed by the Rao algorithms using Kapur function at various threshold levels k = 1, 2, 3, 4, and 5 to the standard benchmark test images. It is realized that the Rao1 algorithm does better thresholds and Jaccard measure compared to the Rao2 and Rao3 algorithms. Table 2 shows the examination of best average objective function values at various threshold levels k = 1, 2, 3, 4, and 5. Higher is the average objective function value, better is the thresholding execution. It is seen that values got utilizing the Rao algorithms are higher when contrasted with different techniques like PSO, FA, ABC, GA, GWO, and SOS. These algorithms are used for the sake of fair comparison in [8].

In this way, the entropy and statistical distribution of the picture histogram can be maximized. Entropy is maximized here, which prompts higher objective function values. The average objective function values increment with increment in the level of thresholds true to form. The number of function assessments increments with more significant levels of thresholding. This is the motivation behind why one watches higher estimations of the average objective function values in Table 2. It is also realized that the Rao1 algorithm does better average fitness function compared to the Rao2 and Rao3 algorithms. To judge the quality of the algorithm to choose multi-thresholds, the Jaccard measure is utilized.

Test Imeses	Methods	Fitness Values					
Test Images		1	2	3	4	5	
	PSO [8]	8.7868	12.2865	15.3744	18.5567	21.2809	
	FA [8]	8.7748	12.2865	15.3928	18.5563	21.3213	
	ABC [8]	8.7868	12.2865	15.3927	18.5445	21.2756	
Cameraman	GA [8]	8.7747	12.2865	15.381	18.5564	21.2792	
	GWO [8]	8.7868	12.2865	15.3942	18.5545	21.3027	
	SOS [8]	8.7868	12.2865	15.3943	18.5567	21.3254	
	Rao1	8.7179	12.1688	15.2224	18.3955	21.1443	
	Rao2	8.7179	12.1688	15.2274	18.3955	21.1443	
	Rao3	8.7179	12.1678	15.2238	18.3955	21.1427	
	PSO [8]	9.1423	12.6346	15.6887	18.5216	21.273	
Donnors	FA [8]	9.1423	12.6346	15.6887	18.5354	21.2817	
reppers	ABC [8]	9.1423	12.6346	15.6885	18.5238	21.2446	
	GA [8]	9.1423	12.6346	15.6883	18.5229	21.2755	

 Table 2.Comparison of average objective function values acquired using various optimization algorithms based on Kapur's entropy.

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	GWO [8]	9.1423	12.6346	15.6886	18.5354	21.2766
	SOS [8]	9.1423	12.6346	15.6887	18.5392	21.2818
	Rao1	9.1700	12.6782	15.7569	18.6633	21.4167
	Rao2	9.1700	12.6782	15.7569	18.5869	21.4167
	Rao3	9.1700	12.6782	15.7569	18.5869	21.4167
	PSO [8]	9.0648	12.5935	15.655	18.5555	21.3769
	FA [8]	9.0648	12.5935	15.655	18.5555	21.4604
	ABC [8]	9.0648	12.5935	15.654	18.5476	21.3940
Ostrich	GA [8]	9.0648	12.5935	15.6547	18.5528	21.4068
	GWO [8]	9.0648	12.5935	15.6548	18.547	21.4547
	SOS [8]	9.0648	12.5935	15.6550	18.5563	21.4613
	Rao1	9.0728	12.6125	15.6722	18.603	21.5343
	Rao2	9.0728	12.6125	15.6722	18.594	21.5343
	Rao3	9.0728	12.6125	15.5569	18.594	21.5343
	PSO [8]	9.2252	12.6227	15.7331	18.6951	21.3700
	FA [8]	9.2252	12.6227	15.7369	18.6949	21.3716
	ABC [8]	9.2252	12.6227	15.7364	18.6896	21.3488
Flower	GA [8]	9.2252	12.6227	15.7364	18.6936	21.3670
	GWO [8]	9.2252	12.6227	15.7362	18.6941	21.3677
	SOS [8]	9.2252	12.6227	15.7369	18.6951	21.3719
	Rao1	9.2911	12.761	15.9073	18.8936	21.5970
	Rao2	9.2911	12.761	15.9073	18.8962	21.5975
	Rao3	9.2911	12.761	15.9073	18.8962	21.5979
	PSO [8]	8.1580	11.0739	13.8912	16.6455	19.1482
	FA [8]	8.1580	11.0774	13.9522	16.6648	19.1448
	ABC [8]	8.1580	11.0774	13.9571	16.6311	19.0740
Plane	GA [8]	8.1580	11.0758	13.9406	16.6390	19.1279
	GWO [8]	8.1580	11.0774	13.9574	16.6497	19.1290
	SOS [8]	8.1580	11.0774	13.9586	16.6705	19.1478
	Rao1	8.2231	11.1549	14.0409	16.7627	19.2301
	Rao2	8.2231	11.1549	14.0409	16.7627	19.2301
	Rao3	8.2231	11.1549	14.0409	16.7627	19.2221
	PSO [8]	8.6091	11.9353	15.0761	17.8740	20.6819
	FA [8]	8.6091	11.9340	15.0761	17.8733	20.694
	ABC [8]	8.6091	11.9353	15.0751	17.8607	20.6371
Girl	GA [8]	8.6091	11.9353	15.076	17.8727	20.6716
	GWO [8]	8.6091	11.9353	15.0735	17.8695	20.6873
	SOS [8]	8.6091	11.9353	15.0761	17.8735	20.6977
	Rao1	8.6681	12.0151	15.1832	18.0532	20.8845
	Rao2	8.6681	12.0151	15.1832	18.0532	20.8845
	Rao3	8.6681	12.0151	15.1792	18.0528	20.8845

5. Conclusion

This paper addresses the Rao algorithms based solution technique for taking care of Kapur entropy issues in MT. The proposed technique is executed on standard benchmark test pictures are taken for the examination to show its efficacy. The benefited solution gives the maximized entropy and statistical distribution of the picture histogram that guarantees the best thresholding. The numerical outcomes are contrasted and the current writing techniques that show the proposed technique is increasingly powerful in finding the global optimal solution for image thresholding issues. The Rao algorithms are appropriate for thresholding of any size and give the greatest average objective function values for standard benchmark test pictures and Rao1 is does better than Rao2 and Rao3 algorithms. The empowering simulation results show that the proposed approach is fit for getting progressively efficient, excellent solutions, stable combination attributes, and great computational efficiency. In the future, this algorithm can be applied for other entropy measures.

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