Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 7, July, 2021:1515 – 1525

Multilevel Image Thresholding Based on Exchange Market Algorithm

S.Anbazhagan [a], M.Veerappan [b]

[a,b] Department of Electrical Engineering, FEAT, Annamalai University, Annamalai Nagar, India

[a] s.anbazhagan@gmx.com

Abstract

With a rapid expansion of image segmentation throughout the decades, the development of scientific optimization as image segmentation is enormous in the segmentation. A need to organize the image thresholding arises to help medical imaging, detection, and recognition in making an informed decision about the image. Image segmentation dependent on computational intelligence approaches is utilized online to cluster the clinical imaging into a positive or negative diagnosis. The proposed market exchange algorithm (EMA) is relied upon to quickly get the top-notch optimal thresholds are controlled by maximizing the Kanpur entropy of various classes. Different from previous optimization techniques, EMA has 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 steady for all images even with the increase of the threshold. Numerical outcomes judgment shows that this algorithm is a promising choice for the multilevel image thresholding issue.

Keywords: Kapur's Entropy, Multilevel Thresholding, Exchange Market Algorithm

1. Introduction

Thresholding is a strategy broadly utilized in image partition. The objective of thresholding is to choose a threshold an incentive to partition the image space into significant regions. 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 suitable threshold values are found by maximizing or minimizing a rule. The well known Otsu's technique [3], threshold are controlled by maximizing the between-class variance. In Kapur's entropy [4], the ideal thresholds are accomplished by maximizing the entropy of various classes. A fuzzy entropy measure is applied for picking the ideal thresholds in [5] while Qiao et al. [6] figured the thresholding rule by investigating the information as far as intensity contrast. Scientists have additionally built up some other best criteria, including fuzzy similarity measure [7], cross-entropy [8], Tsallis entropy [9], Bayesian error [10], Renyi's entropy [11], 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 strategy has an undeniable downside in that the computational complexity nature increments exponentially with an increase in the number of required thresholds. To a limited degree, this confines its application in MT, various methodologies and comparing upgrades have been proposed to dispose of the previously mentioned disadvantages.

Hammouche et al. [12] concentrated on taking care of the image thresholding issue by consolidating between-class variance rule with metaheuristic systems, for example, genetic algorithm, particle swarm optimization (PSO), differential evolution (DE), ant colony optimization (ACO), simulated annealing (SA) and Tabu search (TS). The improved bat algorithm [13] embraced to scan for multilevel threshold utilizing Kapur criteria, gives better outcomes contrasted with PSO, DE, cuckoo search (CS), firefly algorithm (FA) and bat algorithm (BA).

The Brownian distribution guided FA by SriMadhava Raja et al. [14] is embraced for taking care of the MT image thresholding issue utilizing Otsu's between-class variance strategy. The proposed method is tried on standard test pictures and contrasted and the conventional FA and Levy flight guided FA. The harmony search (HS) multi thresholding calculation consolidates the first HS calculation and the Kapur's system [15]. The modified PSO is applied to taking care of MT issues dependent on Otsu's technique [16].

The spiders can impart their data to other bugs to pick up the social information. This social spider procedure is to locate the ideal threshold an incentive if there should be an occurrence of multilevel thresholding. The consequences of this methodology are contrasted with the PSO system [17].

Empowered by the effective utilization of the flower pollination (FP) and Social spider optimization (SSO) calculations, this paper [18] further analyzes their achievability for taking care of picture thresholding issue through an MT approach. As an objective function, Kapur's entropy is utilized to look at the best execution of thresholding pictures utilizing these two optimizations. Acquired outcomes from SSO and FP have been thought about against the PSO and the BAs.

The FA has been applied to upgrading the productivity of multilevel image thresholding. In any case, now and again, FA is handily caught into nearby optima. The principle thought of improved FA (IFA) is adaptively picking one procedure to assist fireflies with finding the optima as per diverse stagnation stations. Also, the multilevel Otsu objective function is studied as the fitness function, and the IFA is applied to glancing through multilevel thresholds [19]. So as to maximize Kapur's objective function, a spider monkey optimization algorithm is utilized. The standard pictures are pre-tried and contrasted and PSO [20]. Panda et al. [21] present an evolutionary gray gradient method for ideal MT of brain magnetic resonance images dependent on Otsu's basis.

The point of whale optimization and moth-flame optimization methods is to decide the best thresholds that maximize the Kapur function. The test consequences of the proposed techniques have been with various swarm methods [22]. Grey wolf optimizer is enlivened from the social and chasing conduct of the grey wolves. This metaheuristic method is applied to MT issues utilizing Kapur entropy function. The exhibitions of the proposed strategy are then contrasted and improved adaptations of PSO and bacterial foraging optimization based MT strategies [23].

The proposed exchange market algorithm (EMA) is a technique explicit, less parameter 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 EMA until an end basis is fulfilled. The consequences of the EMA 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 EMA method 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. Multilevel Image Thresholding 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], [13], [23] for additional subtleties.

The Proposed Algorithm for MT

Optimization is the way toward improving something than the past structure. In the course of the most recent decade, the total intelligent conduct of insect or animal groups in the normal world for instance flocks of birds, colonies of ants, schools of fish, swarms of bees, and termites have intrigued the enthusiasm of scientists. The aggregate activity of insects, birds, or animals is distinguished as swarm conduct. Numerous specialists have utilized swarm conduct as a system for taking care of entangled real-world issues. Furthermore, all the intelligence techniques require the tuning of parameters for them to work properly. To avoid this difficulty, an optimization method, EMA, an adjustable parameter algorithm, is implemented in this paper to solve complex MT problems.

Mathematical Model of EMA

EMA method is a global optimization technique initially created by Ghorbani and Babaei [24]. Be that as it may, EMA has two proficient and ground-breaking searching through operators and two absorbent operators. Subsequently, the random numbers' generation and association are acted in the best structure in this algorithm prompts exceptionally improvement of the other algorithm' restrictions. EMA is suitable for continuous nonlinear optimization challenges. The proposed algorithm is motivated by shares exchanged on the stock exchange market and it is known as the EMA. Because of its basic idea and high proficiency, EMA has become an extremely appealing optimization procedure and has been effectively applied to numerous real-world issues [25], [26], [27], [28].

The Exchange Market under Balanced Conditions

The market is accepted in an ordinary state with no impressive wavering and the investors attempt to pick up the greatest potential advantages without performing non-market risks by utilizing the encounters of effective investors. In this manner, they rival one another. Here, any individual is positioned in three gatherings by numbering the shares from any sort as indicated by the objective function. The gatherings are known as the primary, mean, and the final person of investors' population [24].

The First Group - Investors with High Rank.This gathering structures the most elevated positioned individuals of the rundown, who don't change their shares with any risk and exchange to keep their position in population. 10-30% is these members. The individuals from this gathering are the tip-top individuals from the exchange market and the best answers are required without confronting any variety [25].

The Second Group - Shareholders with Mean Rank.These gatherings structure the center-positioned individuals and use the distinctions of the diverse first gathering individuals' shares amounts. The individuals of this gathering are accountable for looking around the optimum point in the optimization issues. This gathering of investors structures 20–half of market exchange vendors. To analyze the people's shares in the primary gathering, it is necessitated that the correlation is done at any rate between two people. For example, on the off chance that one for every child in the main gathering imparts x to the estimation of a unit and a someone else in a similar gathering has a similar share with the worth b, the jth individual in the subsequent gathering utilizes the distinction of two investors in the primary gathering and chooses share x with an incentive among a and b. The choice of these two people from the first gathering is randomly done [26]. As needs are, to assess the distinctions among all portions of these two investors in the first and second gatherings' people, change their shares' estimation of any kind dependent on equation (1) to arrive at more advantages:

$$pop_j^{group(2)} = r \times pop_{1,i}^{group(1)} + (1-r) \times pop_{2,i}^{group(1)} \qquad (1)$$

$$i = 1, 2, 3, \dots, n_i \text{ and } j = 1, 2, 3, \dots, n_j$$

where n_i is the n^{th} individual of the first gathering, n_j is the n^{th} individual of the second gathering and r is a random number in interval [0, 1]. $pop_{1,i}^{group(1)}$ and $pop_{2,i}^{group(1)}$ are the ith person of the first group and $pop_j^{group(2)}$ is the j^{th} person of the second group.

The Third Group - Shareholders with Weak Rank.The people in this gathering have less fitness in correlation with the second gathering. At that point to acquire more advantages they select shares like the primary gathering and with a higher risk in examination with the second gathering. Not at all like second gathering people, they use the distinctions of shares estimations of the primary gathering just as their share qualities' disparities contrasted with the primary bunch people and change their shares. To look at the primary gathering's shares, it is necessitated that the correlation is done between two investors. To expand this present gathering's people chance in correlation with the second gathering, two random variables are utilized instead of factor 1 which it's normal worth is about equivalent to one [27].

Thusly, this present gathering's people change their shares' estimation of any kind dependent on equation (2) to arrive at more advantages:

$$S_k = 2 \times r_1 \times \left(pop_{i,1}^{group(1)} - pop_k^{group(3)}\right) 2 \times r_1 \times (pop_{i,2}^{group(1)} - pop_k^{group(3)}) \quad (2)$$

$$pop_k^{group(3),new} = pop_k^{group(3)} + 0.8 \times S_k \quad (3)$$

where r_1 and r_2 are random numbers in interval [0, 1] and n_k is the n[th] member of the third group. $pop_k^{group(3)}$ is the k[th] member and S_k is the share variations of the k[th] member of the third group.

The individuals from this gathering search the optimum focuses around the optimum point in more extensive territory than that of the second gathering individuals. This gathering contains 20–half of the complete market population.

The Exchange Market in Oscillation State

In some cases, the stock exchange falls in the oscillating state because of political and conservative practices of money related associations or nations. In this condition, after reassessment of investors and positioning the individuals in gatherings, the investors make their best to achieve some serious yet insightful risks so as to pick up the greatest conceivable benefit and to accomplish high market rankings from an objective function perspective. Here, every part takes an alternate financial approach that relies upon the picked up benefit and achieves a few risks to outperform the market best part. The individuals can be ordered into three gatherings as indicated by their performance [28].

The First Group - Investors with High Rank.This piece of the population shapes the first-class individuals from the exchange market or the best answers to the optimization issue. This gathering structures 10–30% of the absolute market population [24].

The Second Group - Shareholders with Mean Rank.These individuals attempt to locate the best expense by changing their shares amounts. The risk level of these investors is extraordinary and increments as their ranks decrease. In this gathering, the all-out share estimations of the individuals are steady and only a piece of the shares esteem increment and the other part faces with decreasing such that the all-out share estimation of any part doesn't at last differ [25]. At first, the quantity of certain shares of every member increments as follows:

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \quad (4)$$

$$\mu = \frac{t_{pop}}{n_{pop}} \quad (5)$$

$$n_{t1} = \sum_{y=1}^{n} s_{ty}\, , y = 1, 2, 3, \dots, n \quad (6)$$

$$\eta_1 = n_{t1} \times g_1 \quad (7)$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{iter_{max}} \times k \quad (8)$$

where Δn_{t1} is the measure of offers ought to be added randomly to certain shares, n_{t1} is all out shares of t[th] part before applying the share changes. s_{ty} is the shares of the t[th] member, δ is the data of exchange market. *r* is an random number in interim [0, 1]. η_1 is chance level identified with every individual from the second gathering, t_{pop} is the quantity of the t[th] member in exchange market. n_{pop} is the quantity of the last member in exchange market, μ is a constant coefficient for every member and g_1 is the basic market chance sum which decreases as iteration number increments. $iter_{max}$ is the last iteration number and k is the quantity of program iteration. $g_{1,max}$ and $g_{1,min}$ demonstrates the most extreme and least estimations of risk in market, individually.

The activity is such that a level of Δn_{t1} value is added randomly to one of the shares utilizing rand order and this proceeds until Δn_{t1} is totally added to at least one shares. Clearly this activity is performed just on shares whose worth can be increased thinking about the constraints and limitations of the exchange market. As referenced, δ is the market data and its reality is significant in optimization issues and results in intelligence and quick convergence of the function to its optimum value. Two distinct conditions exist to choose δ dependent on market data [26].

Some data about market circumstance is close by. This case is gotten in issues that the penalty factor is utilized. The δ esteem is equivalents to the expected or the problem data. In this condition, there is no compelling reason to utilize penalty factor and the search procedure falls just in the logical area [24]. The nearness of $\delta = n_{t1}$ causes every member's all out share worth equivalent to the problem's constant value (absolute estimations of the problem varieties is constant).

No data about market circumstance is close by. In this condition, δ is an equivalent to add up to shares estimation of every member in no market oscillation condition [25]. At the end of the day, δ equivalents to Δn_{t2} (this condition is used in standard functions optimization).

The μ is the risk increment coefficient and makes lower ranked investors from objective function perspective perform more risks in contrast with the more effective individuals with increment their account. g_1 is the variable risk coefficient and decides investors should change what level of their shares. The measure of this parameter fluctuates in various issues and its variety extends by and large falls in [0, 1]. In the essential iterations, g_1 has its maximum value and decreases as the iteration number increments. This coefficient can be planned such that it doesn't rely upon the iteration and decreases with a constant or exponential slop [26].

In the second part of this procedure, it is basic that each part's total share amount resembles the past state. Hence, every member should sell a similar measure of his shares he has recently purchased to even out every member's share amount with that of the essential state. It is necessitated that every member at long last decreasing Δn_{t2} of his share amount. Here Δn_{t2} is as follows:

$$\Delta n_{t2} = n_{t2} - \delta \tag{9}$$

where Δn_{t2} is the measure of shares ought to be decreased randomly from certain shares and n_{t2} is the absolute share measure of tth member in the wake of applying the share varieties.

As it is self-evident, if the market faces oscillation and there is no data about the market circumstance, a few individuals sell arbitrarily a few pieces of their shares, and some purchase randomly new shares equivalent to the sold amount with no adjustment in the absolute share of the overall market amount. In that capacity, the assurance of a stock ought to be sold is acted in random. The choice of the number of shares that ought to be decreased is likewise done randomly. For this situation, every member gets a few shares from any kind randomly and sells the equivalent measure of the purchased amount from any share type in continuous. This empowers investors to change a portion of their shares without changing their all-out share value [24].

The Third Group - Shareholders with Weak Rank.These individuals attempt to discover better expense by changing they are all out share amounts. The risk level of these individuals is extraordinary and increments as their ranking decrease. In this gathering, the all-out share number of individuals varies and is included a solitary part, in contrast to the past section [25]. Here, the investors attempt to discover another and obscure blend of shares and they differ the quantity of a portion of their shares as follows:

$$\Delta n_{t3} = (4 \times r_s \times \mu \times \eta_2) \tag{10}$$

$$r_s = (0.5 - rand) \tag{11}$$

$$\eta_2 = n_{t1} \times g_2 \tag{12}$$

where Δn_{t3} is the share amount ought to be randomly added to the portions of every member, r_s is an random number in $[-0.5, 0.5]$ and η_2 is the risk coefficient identified with every individual from the third group. g_2 is the variable risk of the market in the third gathering and μ is the risk increment coefficient which powers lower ranked investors from objective function perspective to perform more risk in contrast with effective contenders with increment their money. g_2 is the variable risk coefficient of the market and figures out what level of shares ought to be changed by investors. The measure of g_2 is within [0, 1]. In the essential iteration, g_2 has its most extreme value and decreases as iteration number increments.

In this section, the individuals exchange a piece of their shares randomly. As it is self-evident, the individuals in this procedure don't rely upon the expense or benefit of every member and rely just upon the number of shares. In this way, the individuals can share until the end of the iteration and the algorithm discovers the better optimum points even with little variations. The perfect state will be discovered by choosing proper market initial values and appropriate algorithm iteration number [26].

EMA Execution Procedure for Taking Care of MT Problem

The methods connected with the execution of EMA [24] for dealing with MT issue are as per the following:

Step 1: Read the standard benchmark test image and instate EMA parameters, for example, choosing initial values and crediting stock to initial investors.

Step 2: Estimating the investors' objective function of Kapur entropy and ranking them.

Step 3: Applying changes on the shares of the second gathering in balance market situation based on the equation (1).

Step 4: Applying changes on shares of third gathering individuals in a balanced market situation based on the equation (3).

Step 5: Estimating the investors' objective function again and ranking them accordingly.

Step 6: The exchange shares of second gathering individuals using the equation (3) under market oscillation condition.

Step 7: The exchange shares of third gathering individuals utilizing the equation (10) under market oscillation condition.

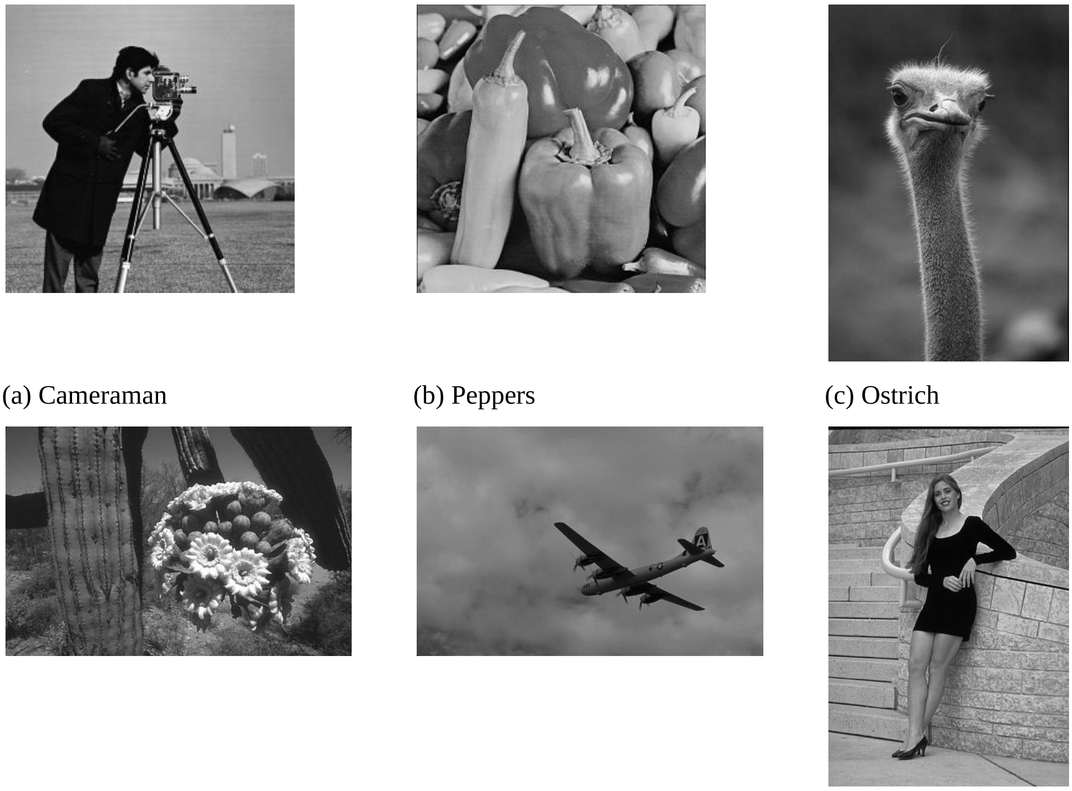
Step 8: Go to step 2 if the program's end conditions are not fulfilled.

Experiments and Results

In this section, the condition of the analyses for the proposed method is presented. The depiction of benchmark pictures is presented right off the bat, at that point, the parameters set for the EMA method are represented quickly and the quality measurements are utilized to assess the nature of the thresholding procedure.

Benchmark Images

The six standard benchmark test pictures are three 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 (b) Peppers (c) Ostrich

(d) Flower (e) Plane (f) Girl

Fig.1. The standard benchmark test images.

Experimental Settings

In this section, tests are done on benchmark gray-scale pictures, Cameraman, Peppers, Ostrich, Flower, Plane, and Girl (refer to Fig. 1), with the size of 256×256, 256×256, 321×481, 481×321, 481×321, and 321×481, respectively, and the Jaccard metric (equation 13) [29] are utilized to look at image thresholding execution.

The application and execution of the EMA method 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.

The tests were completed on an HCL Laptop with an Intel Core i5 (2.40GHz) processor and 4GB memory. All the techniques are implemented in "Matlab2015" and actualized on Windows 7 - 32 bits.

Cameram an   Peppe rs   Ostric h   Flower   Plane   Girl

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

Segmented Image Quality Metrics

To judge the quality of the algorithm to choose multi-thresholds, the Jaccard measure is utilized.

$$Jac = \frac{|I_{original} \cap J_{segmentedimage}|}{|I_{original} \cup J_{segmentedimage}|} \tag{13}$$

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.

Table 1. Optimal threshold and Jaccard measures gained by the proposed EMA algorithm.

Test images	k	Thresholds	Jac
Cameraman	1	193	0.02
	2	128, 193	0.60
	3	44, 101, 193	0.78
	4	38, 96, 145, 195	0.78

Test images	k	Thresholds	Jac
	5	24, 61, 96, 146, 196	0.81
Peppers	1	80	0.78
	2	74, 147	0.81
	3	58, 111, 165	0.86
	4	58, 101, 146, 195	0.86
	5	43, 79, 122, 155, 196	0.90
Ostrich	1	127	0.08
	2	119, 180	0.10
	3	75, 122, 180	0.53
	4	30, 76, 120, 188	0.99
	5	30, 75, 118, 158, 196	0.99
Flower	1	137	0.10
	2	118, 181	0.16
	3	78, 130, 188	0.51
	4	72, 117, 158, 204	0.57
	5	65, 107, 140, 177, 215	0.63
Plane	1	84	0.93
	2	66, 101	0.95
	3	35, 72, 102	0.96
	4	35, 71, 101, 158	0.96
	5	33, 66, 96, 119, 160	0.96
Girl	1	109	0.78
	2	106, 202	0.80
	3	94, 143, 202	0.85
	4	37, 85, 143, 202	0.91
	5	36, 84, 132, 175, 207	0.91

3. The Results and Discussions

Since EMA is stochastic, it is important to utilize a proper statistical measurement to quantify its efficiency. To keep up similarity with comparable works detailed in the writing [30], 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 EMA technique.

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

Test images	*k*	Fitness values						
		PSO [30]	FA [30]	ABC [30]	GA [30]	GWO [30]	SOS [30]	EMA
Cameraman	1	8.7868	8.7748	8.7868	8.7747	8.7868	8.7868	8.7179
	2	12.2865	12.2865	12.2865	12.2865	12.2865	12.2865	12.1688

Test images	*k*	Fitness values						
		PSO [30]	FA [30]	ABC [30]	GA [30]	GWO [30]	SOS [30]	EMA
	3	15.3744	15.3928	15.3927	15.381	15.3942	15.3943	15.2224
	4	18.5567	18.5563	18.5445	18.5564	18.5545	18.5567	18.3765
	5	21.2809	21.3213	21.2756	21.2792	21.3027	21.3254	21.3303
Peppers	1	9.1423	9.1423	9.1423	9.1423	9.1423	9.1423	9.1700
	2	12.6346	12.6346	12.6346	12.6346	12.6346	12.6346	12.6782
	3	15.6887	15.6887	15.6885	15.6883	15.6886	15.6887	15.7569
	4	18.5216	18.5354	18.5238	18.5229	18.5354	18.5392	18.6482
	5	21.273	21.2817	21.2446	21.2755	21.2766	21.2818	21.3853
Ostrich	1	9.0648	9.0648	9.0648	9.0648	9.0648	9.0648	9.0728
	2	12.5935	12.5935	12.5935	12.5935	12.5935	12.5935	12.6125
	3	15.6550	15.6550	15.6540	15.6547	15.6548	15.6550	15.6711
	4	18.5555	18.5555	18.5476	18.5528	18.5470	18.5563	18.5906
	5	21.3769	21.4604	21.394	21.4068	21.4547	21.4613	21.5181
Flower	1	9.2252	9.2252	9.2252	9.2252	9.2252	9.2252	9.2911
	2	12.6227	12.6227	12.6227	12.6227	12.6227	12.6227	12.7610
	3	15.7331	15.7369	15.7364	15.7364	15.7362	15.7369	15.9073
	4	18.6951	18.6949	18.6896	18.6936	18.6941	18.6951	18.8886
	5	21.3700	21.3716	21.3488	21.3670	21.3677	21.3719	21.5827
Plane	1	8.1580	8.1580	8.1580	8.1580	8.1580	8.1580	8.2231
	2	11.0739	11.0774	11.0774	11.0758	11.0774	11.0774	11.1549
	3	13.8912	13.9522	13.9571	13.9406	13.9574	13.9586	14.0409
	4	16.6455	16.6648	16.6311	16.639	16.6497	16.6705	16.7582
	5	19.1482	19.1448	19.074	19.1279	19.1290	19.1478	19.2097
Girl	1	8.6091	8.6091	8.6091	8.6091	8.6091	8.6091	8.6681
	2	11.9353	11.934	11.9353	11.9353	11.9353	11.9353	12.0151
	3	15.0761	15.0761	15.0751	15.076	15.0735	15.0761	15.1832
	4	17.874	17.8733	17.8607	17.8727	17.8695	17.8735	18.0475
	5	20.6819	20.694	20.6371	20.6716	20.6873	20.6977	20.8530

From Table 1, the optimal thresholds together with the Jaccard measures are computed by the EMA using Kapur function at various threshold levels k = 1, 2, 3, 4, and 5 to the standard benchmark test images. 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 EMA are higher when contrasted with different techniques like PSO, FA, artificial bee colony (ABC), genetic algorithm (GA), grey wolf optimizer (GWO), and Symbiotic Organisms Search (SOS). These algorithms are used for the sake of fair comparison in [30]. 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. To judge the quality of the algorithm to choose multi-thresholds, the Jaccard measure is utilized.

4. Conclusion

This paper addresses the EMA 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 so as 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 EMA is appropriate for thresholding of any size and gives the greatest average objective function values for standard benchmark test pictures. 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 to other entropy measures..

References

[1] S. Dey, S. Bhattacharyya and U. Maulik, "Quantum behaved multi-objective PSO and ACO optimization for multi-level thresholding," in Proceedings of the International Conference on Computational Intelligence and Communication Networks, Bhopal, IEEE, 2014, pp. 242-246.

[2] A. K. Bhandari, A. Kumar and G. K. Singh, "Tsallis entropy based multilevel thresholding for colored satellite image segmentation using evolutionary algorithms," Expert Systems with Applications, Vol. 42, No. 22, December 2015, pp. 8707-8730.

[3] N. Otsu, "A threshold selection method from gray-level histograms," IEEE Transactions on Systems, Man, and Cybernetics, Vol. 9, No. 1, January 1979, pp. 62-66.

[4] J. N. Kapur, P. K. Sahoo and A.K. Wong, "A new method for gray-level picture thresholding using the entropy of the histogram," Computer Vision, Graphics, and Image Processing, Vol. 29, No. 3, March 1985, pp. 273-285.

[5] L. K. Huang and M. J. J. Wang, "Image thresholding by minimizing the measures of fuzzi-ness," Pattern Recognition, Vol. 28, No. 1, January 1995, pp. 41-51.

[6] Y. Qiao, Q. Hu, G. Qian, S. Luo and W. L. Nowinski, "Thresholding based on variance and intensity contrast," Pattern Recognition, Vol. 40, No. 2, February 2007, pp. 596-608.

[7] X. Li, Z. Zhao and H. D. Cheng, "Fuzzy entropy threshold approach to breast cancer detec-tion," Information Sciences-Applications, Vol. 4, No. 1, July 1995, pp. 49-56.

[8] C. H. Li and P. K. S. Tam, "An iterative algorithm for minimum cross entropy thresholding," Pattern Recognition Letters, Vol. 19, No. 8, June 1998, pp. 771-776.

[9] K. Li and Z. Tan, "An Improved Flower Pollination Optimizer Algorithm for Multilevel Image Thresholding," IEEE Access, Vol. 7, November 2019, pp. 165571-165582.

[10] J. Kittler and J. Illingworth, "Minimum error thresholding," Pattern Recognition, Vol. 19, No. 1, January 1986, pp. 41-47.

[11] S. Zarezadeh and M. Asadi, "Results on residual Rényi entropy of order statistics and record values," Information Sciences, Vol. 180, No. 21, November 2010, pp. 4195-4206.

[12] K. Hammouche, M. Diaf and P. Siarry, "A comparative study of various meta-heuristic techniques applied to the multilevel thresholding problem," Engineering Applications of Ar-tificial Intelligence, Vol. 23, No. 5, August 2010, pp. 676-688.

[13] A. Alihodzic and M. Tuba, "Improved bat algorithm applied to multilevel image thresholding," The Scientific World Journal, 2014.

[14] N. Sri Madhava Raja, V. Rajinikanth and K. Latha, "Otsu based optimal multilevel image thresholding using firefly algorithm," Modelling and Simulation in Engineering, 2014.

[15] D. Oliva, E. Cuevas, G. Pajares, D. Zaldivar and M. Perez-Cisneros, “Multilevel thresholding segmentation based on harmony search optimization,” Journal of Applied Mathematics, 2013.

[16] Y. Liu, C. Mu, W. Kou and J. Liu, "Modified particle swarm optimization-based multilevel thresholding for image segmentation," Soft Computing, Vol. 19, No. 5, May 2015, pp. 1311-1327.

[17] P. Agarwal, R. Singh, S. Kumar and M. Bhattacharya, "Social spider algorithm employed multi-level thresholding segmentation approach," in Proceedings of the International Confe-rence on Information and Communication Technology for Intelligent Systems, Charm, Springer, 2016, pp. 249-259.

[18] S. Ouadfel and A. Taleb-Ahmed, "Social spiders optimization and flower pollination algo-rithm for multilevel image thresholding: a performance study," Expert Systems with Appli-cations, Vol. 55, August 2016, pp. 566-584.

[19] K. Chen, Y. Zhou, Z. Zhang, M. Dai, Y. Chao and J. Shi, "Multilevel image segmentation based on an improved firefly algorithm," Mathematical Problems in Engineering, 2016.

[20] S. S. Pal, S. Kumar, K. Kashyap, Y. Choudhary and M. Bhattacharya, "Multi-level thre-sholding segmentation approach based on spider monkey optimization algorithm," in Pro-ceedings of the International Conference on Computer and Communication Technologies, New Delhi, Springer, 2016, pp. 273-287.

[21] R. Panda, S. Agrawal, L. Samantaray and A. Abraham, "An evolutionary gray gradient algo-rithm for multilevel thresholding of brain MR images using soft computing techniques," Ap-plied Soft Computing, Vol. 50, January 2017, pp. 94-108.

[22] M.A. El Aziz, A.A. Ewees and A.E. Hassanien, "Whale optimization algorithm and moth-flame optimization for multilevel thresholding image segmentation," Expert Systems with Applications, Vol. 83, October 2017, pp. 242-256.

[23] A.K.M. Khairuzzaman and S. Chaudhury, "Multilevel thresholding using grey wolf optimizer for image segmentation," Expert Systems with Applications, Vol. 86, November 2017, pp. 64-76.

[24] N. Ghorbani and E. Babaei, "Exchange market algorithm," Applied Soft Computing, Vol. 19, June 2014, pp. 177-187.

[25] N. Ghorbani, "Combined heat and power economic dispatch using exchange market algo-rithm," International Journal of Electrical Power & Energy Systems, Vol. 82, November 2016, pp. 58-66.

[26] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," In-ternational Journal of Electrical Power & Energy Systems, Vol. 75, February 2016, pp. 19-27.

[27] A. Rajan and T. Malakar, "Exchange market algorithm based optimum reactive power dis-patch," Applied Soft Computing, Vol. 43, June 2016, pp. 320-336.

[28] A. Rajan and T. Malakar, "Optimum economic and emission dispatch using exchange market algorithm," International Journal of Electrical Power & Energy Systems, Vol. 82, November 2016, pp. 545-560.

[29] M. A. Elaziz, A. A. Ewees and A. E. Hassanien, "Hybrid swarms optimization based image segmentation," in Proceedings of the Hybrid Soft Computing for Image Segmentation, Charm, Springer , 2016, pp. 1-21.

[30] B. Küçükuğurlu and E. Gedikli, "Symbiotic Organisms Search Algorithm for multilevel thresholding of images," Expert Systems with Applications, Vol. 147, June 2020, pp. 113210.