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Kapur's Entropy and Cuckoo Search Algorithm Assisted Segmentation and Analysis of RGB Images

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Abstract

Background/Objectives: In this paper, Cuckoo Search (CS) algorithm based image multi-thresholding is proposed for optimal segmentation of RGB image by maximizing the entropy value in Kapur's method. **Methods/Statistical Analysis:** The aim of the paper is to search for an optimized threshold value for image segmentation using CS algorithm where fitness function is designed based on entropy of the image. The capability of CS assisted segmentation with Kapur's function is established in comparison with Firefly and PSO optimization algorithms using the universal image superiority measures existing in the literature. **Findings:** Results of this study show that CS with Kapur's function offers better performance measure, whereas Firefly and PSO optimization algorithms offers earlier convergence with comparatively lower CPU time. **Applications/Improvements:** In future, proposed method can be implemented for the medical image analysis.

Keywords: Cuckoo Search Algorithm, Image Segmentation, Kapur's Entropy, Noise Stain, RGB Image

1. Introduction

A human eye differentiates around thousand shades of grey but in contrast it can differentiate enormous number of colour shades and intensities. Many researchers have revealed that additional features that are not distinguished in gray-level images can be obtained in RGB images. Skarbek et al. embraces techniques involving colour image segmentation such as histogram and clustering. Also, descriptions on a few novel approach and suggestions in the improvement of such algorithm have been discussed. Clearly, from the approach by Pal and Pal of entropic thresholding, only one threshold value is obtained for an image, which leads to segmentation of an image into two regions. This helps in classification of object and background or extraction of an object[1]. But in real time applications, an image needs to be segmented into more than two regions which can be achieved by multi-level thresholding proposed in the work by Suresh kumar et al[2]. Entropy maximization based multilevel thresholding has been implemented in which a set of thresholds is obtained by the local maxima of the entropy.

Based on the concept of entropy to thresholding introduced by Pun[3], Kapur et al. concludes, when the maximum value of the sum of entropies of background and object is reached, threshold is obtained[4]. Also, segmentation of RGB images based on Cuckoo search algorithm shows that, multilevel segmentation based on CS algorithm offers better result when compared to BFO and PSO[5]. From the work of the researchers, the exhaustive search limits multilevel thresholding as the computational complexity increases due to the exponential behaviour. The histograms of gray scale images are always multimodal. There is a complexity in determining the exact position of thresholds in multimodal histograms.

In this work, evolutionary problems have been applied to determine proper threshold values. This improves the efficacy of multilevel thresholding based image segmentation. Results of this study are validated with Firefly Algorithm (FA) and Particle Swarm

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Optimization (PSO) based segmentation procedures. The quality measures of the resulting image and the test image is obtained by the bivariate measures[6]. Image quality measures, such as Root Mean Square Error (RMSE), Pixel to Signal Noise Ratio (PSNR), Normalised Cross Correlation (NCC), Average Difference (AD), Structural Content (SC), Mean Difference (MD) and Normalised Absolute Error (NAE) have been used to validate the proposed segmentation technique.

In this paper Section 2, discusses about well-known entropic segmentation method (Kapur's Entropy) to be tested in this paper. Section 3, is an overview of the heuristic algorithms considered. Finally, the experimental results for the image set that is considered along with their histograms, conclusions and future works are discussed in Section 5.

2. Kapur's Function

In this section, a conditional probability entropy method popularly known as Kapur entropy is employed. It was initially proposed in 1985 to segment the gray scale image using the entropy of the histogram[9]. The threshold is obtained when the maximum value of the sum of background and object entropies is reached.

This approach finds the optimal *Th* which maximizes overall entropy. Let, $Th = [th_1, th_2, ..., th_{k-1}]$ is a vector of the image thresholds. The Kapur's entropy will be;

$$J_{\max} = f_{kapur} \quad (Th) = \sum_{j=1}^{k} H_j^C \qquad for \quad C\{1,2,3\} \tag{1}$$

Generally, each entropy is computed independently based on the particular *th* value. For a multi level thresholding problem, it can be resolved by using the following equation;

$$\begin{aligned} H_1^C &= \sum_{j=1}^{th_1} \frac{Ph_j^C}{\omega_0^C} \ln\left(\frac{Ph_j^C}{\omega_0^C}\right), \\ H_2^C &= \sum_{j=th_1+1}^{th_2} \frac{Ph_j^C}{\omega_1^C} \ln\left(\frac{Ph_j^C}{\omega_1^C}\right), \\ &\vdots \\ H_k^C & \sum_{j=th_k+1}^{L} \frac{Ph_j^C}{\omega_{k-1}^C} \ln\left(\frac{Ph_j^C}{\omega_{K-1}^C}\right) \end{aligned} \tag{2}$$

where Ph_j^C - the probability distribution of the intensity levels and $\omega_0^C, \omega_1^C, ...\omega_{k-1}^C$ - probability occurrence for *k* levels. Detailed explanation for the Kapur's function can be found in[14-17].

3. Summary of Heuristic Algorithms

In the proposed work, the Cuckoo search multilevel-thresholding has been implemented for a series of standard RGB image datasets and its performance is then evaluated with the heuristic methods, such as FA and PSO.

- Cuckoo Search

CS is one of the flourishing algorithms, proposed by Yang and Deb[13] in 2009. This algorithm is mainly depends on the reproduction illusion of parasitic cuckoos. CS algorithm is realized based on the following policy:

The mathematical appearance of the CS algorithm used in this study is given below:

$$X_i^{(t+1)} = X_i^{(t)} + \alpha \oplus Levy(\lambda) \tag{3}$$

where $X_i^{(t)}$ is the initial position, $X_i^{(t+1)}$ is the updated position, α is chosen as 1.2 and $\oplus$ is the symbol for entry wise multiplication.

In this work, Levy Flight (LF) based approach is considered to update the position of the agents. LF is a random walk in which the search steps can be drawn using the following Levy distribution[14-16,19]:

$$Levy \sim u = t^{-\lambda} \quad \text{for} \quad (1 < \lambda \le 3) \tag{4}$$

- Firefly Algorithm

The classical FA was initially discussed by Yang[17]. It is a nature-inspired meta-heuristic algorithm, in which flashing illumination patterns generated by invertebrates, such as glowworms and fireflies, were at the essence of its creation. The traditional FA is developed by considering the following conditions[17]. Recently, FA based approach is implemented for the gray scale[20] and RGB[21] image segmentation by the researchers.

The movement of the attracted firefly *i* towards a brighter firefly *j* can be determined by the following position update equation:

$$X_i^{t+1} = X_i^t + \hat{a}_0 e^{-\hat{a}\, d_{ij}^2}(X_j^t - X_i^t) + \alpha_1 .\ \text{sign (rand - 1/2)} \oplus \ \text{L(s)} \tag{5}$$

where X_i^{t+1} is the updated position of firefly, X_i^t is the initial position of firefly, and $\hat{a}_0 e^{-\hat{a}\, d_{ij}^2}(X_j^t - X_i^t)$ may be considered as the attractive force between fireflies.

- Particle Swarm Optimization

PSO is a most successful heuristic approach, widely adopted to solve a variety of engineering optimization problem. Recently, the PSO is also implemented to solve the image multi-level thresholding process[22].

The PSO algorithm has two basic equations such as velocity update and position update equation and are represented as;

$$V_i(t+1) = W^t.V_i^t + C_1R_1(P_i^t - S_i^t) + C_2R_2(G_i^t - S_i^t) \quad (6)$$

$$X_i(t+1) = X_i^t + V_i(t+1) \quad (7)$$

Where W^t is inertia weight assigned as 0.8, V_i^t is the current velocity of particle, $V_i(t+1)$ -updated velocity of particle, X_i^t -current position of particle, $X_i(t+1)$ -updated position of particle, R_1, R_2 are the random numbers [0,1] and C_1 =0.6 and C_2=2.

Initially the CS based optimization search is adopted to find the optimal thresholds for RGB image datasets of size 512 x 512, stained with some well-known noise and its performance measures were compared with the FA and PSO algorithms existing in the literature.

4. Results

Cuckoo search algorithm supervised Kapur's entropy based optimal image multi-level thresholding work is implemented in Matlab R2010a software on an AMD C70 Dual Core 1GHz CPU, 4 GB RAM running with windows 8.

The optimization process is initiated with the following algorithm parameters: population size is 25, dimension of search is *Th*(chosen threshold), maximum number of iteration is fixed as 1000 and maximized objective function (J_{max}) is the guideline to terminate the search process. This procedure is repeated 20 times on each image using the considered images and the mean value of threshold is recorded as the optimal threshold. In this work, the standard 512 x 512 sized RGB test images, such as Mandrill, Lena and Peppers are considered.

In the literature, segmentation is widely applied on the test images, by assuming the noise level as zero. The noisy image segmentation is complex compared with the smooth image, since the histogram patters are greatly disturbed due to the noise. Hence, in this work, the test images are stained using the common noise values, like the Salt & Pepper noise and Speckle noise.

Table 1 presents the considered image dataset and its corresponding histogram values are presented in Table 2. In the histogram, y-axis represents the pixel level and the x-axis represents the RGB levels.

Table 1. 512 x 512 sized RGB image dataset

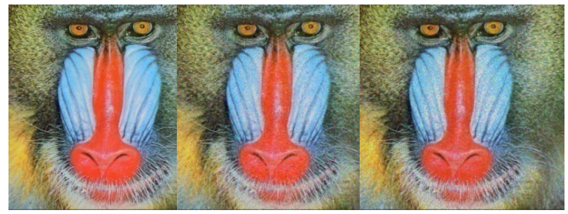
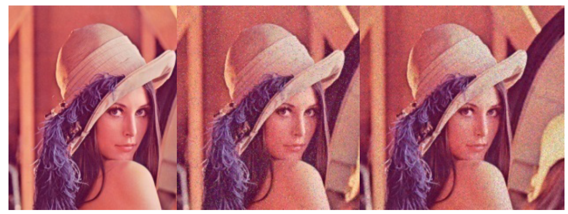
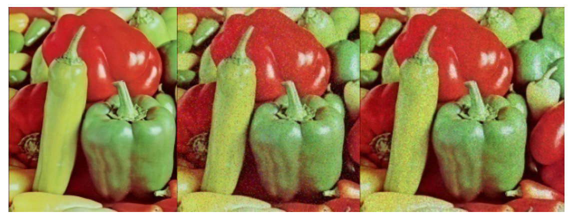
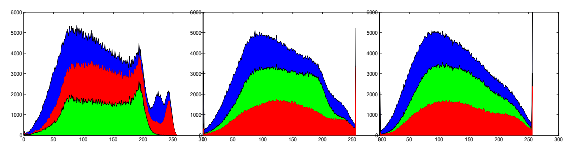
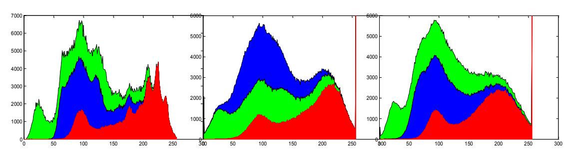
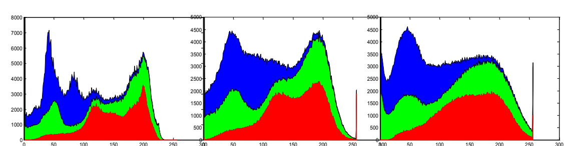
Image	Original	Salt & Pepper	Speckle
Mandrill			
Lena			
Peppers			

Table 2. RGB histogram for smooth and noise stained images

Image	Original	Salt & Pepper	Speckle
Mandrill			
Lena			
Peppers			

Initially the proposed multi-level segmentation process is applied on Mandrill image using CS and Kapur's funtion for *Th*={2,3,4,5}. The thresholded images are depicted in Table 3 and the related threshold values and image quality measures are shown in Table 4. Same procedure is repeated on the considered image dataset using CS optimized Kapur function for *Th*={2,3,4,5} and the results are presented in Table 4.

Table 3. Segmented Mandrill image for Th={2,3,4,5}

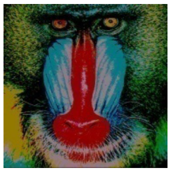
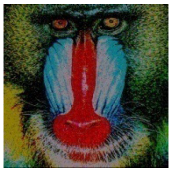
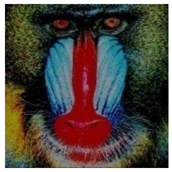
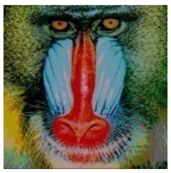
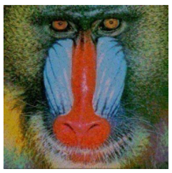
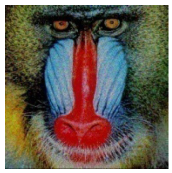
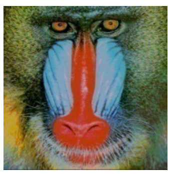
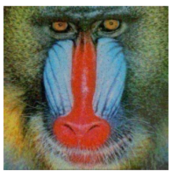
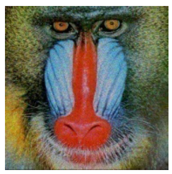
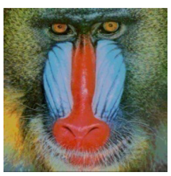
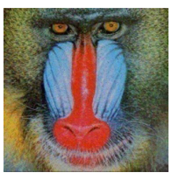
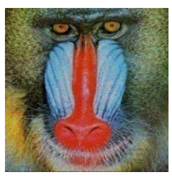
Th	Original	Salt & Pepper	Speckle
2			
3			
4			
5			

Table 4 presents the performance measure values, such as the optimal thresholds and CPU time value between the CS, FA and PSO based methods. From this, it can be noted that the performance measure offered by the proposed method is better than the FA and PSO for smooth and noisy images. From this result, it is concluded that, the CS approach offers better result on the considered RGB test images for Th={2,3,4,5}.

Further, the superiority of the proposed multi thresholding procedure is analysed by considering the image quality measures, such as Root Mean Square Error (RMSE), Pixel to Signal Noise Ratio (PSNR), Normalised Cross Correlation (NCC), Average Difference (AD), Structural Content (SC), Mean Difference (MD) and Normalised Absolute Error (NAE) existing in the literature. Table 5 presents the image quality measure values obtained with the proposed method. The result evident that, the performance measure value will increase, when the Th value increases. The result also confirms the robustness of the proposed segmentation procedure, since the quality measure values for the smooth and noisy images are approximately similar. Similar results are

5. Conclusion

In this paper, RGB image segmentation is proposed using the CS and Kapur's function. The threshold values are chosen as Th={2,3,4,5}. In order to verify the robustness of the proposed work, proposed method is tested using the smooth and most common noise values, such as Salt & Pepper and Speckle noise stained image. Image performance measures, such as objective function and CPU time is initially considered to justify the outcome of CS algorithm with FA and PSO. Later the image quality measures, such as RMSE, PSNR, NCC, AD, SC, MD and NAE are considered. The simulation result confirms that, CS based segmentation helps to achieve better result compared with the FA and PSO on the considered image dataset compared with FA and PSO.

Table 4. Performance measure values

Image	Th		Optimal thresholds	CPU Time (sec)		
				CS	FA	PSO
Original	2	R	146, 186	171.1580	193.2988	197.1834
		G	121,164			
		B	133,177			
	3	R	99,174,219	335.8511	341.2134	350.1036
		G	88,150,182			
		B	93,167,196			
	4	R	67,129,191,226	496.7429	500.1972	503.3309
		G	56,108,160,205			
		B	71,125,186.217			
	5	R	34,88,142,196,240	679.6039	682.1936	688.5317
		G	31,67,116,164,227			
		B	51,100,149,198,249			

Salt & Pepper	2	R	139,188	192.2082	201.3873	196.0153
		G	126,163			
		B	137,182			
	3	R	93,176,195	326.3404	330.1937	330.6311
		G	64,145,175			
		B	91,170,191			
	4	R	61,126,192,218	434.3976	451.3983	448.1036
		G	55,113,170,197			
		B	65,128,187,205			
	5	R	44,96,149,201,242	611.1047	619.1991	628.0544
		G	54,107,161,218,249			
		B	50,101,152,201,236			
Speckle	2	R	142,175	181.9009	201.2883	190.1439
		G	140,182			
		B	137,171			
	3	R	95,175,202	293.7383	297.7004	301.6382
		G	102,180,209			
		B	92,173,196			
	4	R	68,129,190,226	434.3120	452.1064	452.1937
		G	61,125,189,232			
		B	67,134,192,229			
	5	R	48,99,150,201,247	637.6308	644.0005	639.1184
		G	46,94,156,203,239			
		B	52,103,154,205,251			

Table 5. Quality measure values of the CS and Kapur based segmentation

Mandrill	Th	RMSE	PSNR	NCC	AD	SC	MD	NAE
Original	2	67.9778	11.4835	0.5504	64.4011	2.8624	128	0.4970
	3	43.6622	15.3287	0.7261	40.2867	1.8029	98	0.3112
	4	30.8882	18.3350	0.7987	28.5200	1.5414	84	0.2207
	5	27.0436	19.4895	0.8230	24.6827	1.4590	75	0.1914
Salt & Pepper	2	67.4808	11.5472	0.5675	62.9105	2.6570	151	0.4859
	3	42.3790	15.5878	0.7189	39.9011	1.8759	111	0.3083
	4	31.0932	18.2775	0.7971	29.1573	1.5493	77	0.2253
	5	28.0254	19.1798	0.8179	26.1450	1.4763	69	0.2021
Speckle	2	74.5899	10.6772	0.5323	68.8079	2.7744	141	0.5347
	3	48.9183	14.3414	0.7038	44.5333	1.8696	104	0.3465
	4	33.0709	17.7419	0.7877	30.7780	1.5785	83	0.2393
	5	26.9765	19.5111	0.8258	25.2440	1.4487	71	0.1963

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