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Research Article

Grey Scale Histogram based Image Segmentation using Firefly Algorithm

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Abstract

In the present work, optimal multi-level image segmentation is proposed using the Firefly Algorithm (FA). RGB histogram image is considered for both bi-level and multi-level segmentation. Multi-thresholding is used to enhance the information such as intensity, pixels of images based on the chosen threshold. In this work, heuristic algorithm based multi-thresholding such as Otsu's thresholding and Kapur's entropy function is implemented for Gray scale test images. Proposed technique are validated for mostly used benchmark images and the outcome of these algorithms are validated for already determined quality measures which is existing in the literature. The Performance of the gray scale images on Firefly Algorithm is carried out using these parameters, like objective value, PSNR, SSIM. From this paper, it is observed that, the considered heuristic algorithms are efficient to extract the information of image based on the chosen threshold values.

Keywords: Gray scale test image; Segmentation; Otsu; Kapur's function; Firefly Algorithm; Image quality measure.

Introduction

Image segmentation is a procedure [1], used to extract information from original test gray scale images. During the segmentation process, a digital image is separated into multiple regions, pixels or objects, to extract and interpret the relevant information of images. In recent years, this process has used mostly in many key fields, such as remote sensing, medical imaging, pattern recognition, and signal detection. Thresholding is the simplest method of image segmentation which is based on the parametric approach which is complex and time consuming.

The outcome of this process can affect the image quality measurements as well as initial conditions [2,3]. Therefore, non-parametric approaches are preferred to determine the gray scale images from the test images. In this paper, image thresholding is proposed using non-parametric approaches, such as Otsu and Kapur's function [3]. During multi-thresholding process, the desired thresholding level to be preset with an available signal processing scheme, which splits the image into various clusters. In the present work, Firefly Algorithm (FA) based approach [4-8] is proposed to guide the multi-level thresholding process Otsu's and Kapur's entropy function for a chosen threshold level Th={2,3,4,5}. The test images on 512 x 512 pixel sized Gray level images are used for segmentation such as Mandrill, Traffic, Jet, Hunter.

The main aim of the present paper is to determine a comparative analysis of gray scale images between the Otsu's and Kapur's function on Firefly Algorithm. The simulation work is done in MatLab R2013a and determined the image quality measurements [10] such as Root Mean Square Error (RMSE), Peak Signal-To Noise Ratio (PSNR), Optimal Thresholds (OT), MEANR, Structural-Similarity Index Matrix (SSIM).

In the second part of the present paper, we discussed about segmentation methods (Otsu and Kapur's Entropy) to be tested. The third part reviews about the heuristic algorithms. The fourth part describes about the implementation of image segmentation. Finally, the experimental results of the segmented gray images are represented along with their histogram, conclusions and reference papers are discussed in sixth part.

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Problem formulation

In image processing many schemes are used to perform the multi-thresholding process. In this paper, comparative values are analysed between Otsu's and Kapur's function based on firefly algorithm for gray scale images. In Thresholding based approach, the segmentation process finds the optimal threshold, which maximizes the overall entropy values [6,8,11].

OTSU Method

Ostu based image segmentation is first proposed in 1979. Initially it works directly on the grey level histogram [12]. Then it finds the threshold that maximizes between-class variance. This process is already implemented in grey scale image and RGB images respectively.

In the present paper, Otsu approach considered the grey scale images with the aid of grey scale histogram. In the grey scale space, each pixel of image is a mixture of black and white. Segmentation process is based on segmenting the image into multiple segments based on their colour, intensity and texture. The optimal threshold value is selected to separate the desired object from their background by applying a threshold in the segmented image [6].

In Otsu's method we searched for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variance of the two classes:

$$\sigma_{\omega}^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t)$$

ω_0 ,ω_1 are probabilities of the two classes separated by the threshold t and $\sigma_0^2$and σ_1^2 are variance of two classes [13].

The class probability$\omega_{0,1}(t)$ is computed from L histogram:

$$\omega_0(t) = \sum_{i=0}^{t-1} P(i)$$

$$\omega_1(t) = \sum_{i=t}^{L-1} P(i)$$

Otsu minimizes the intra-class variance which is same as maximizing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_{\omega}^2(t)$$
$$= \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2$$
$$= \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2$$

Which is expressed in terms of class probabilities ω and class means μ.

The class means $\mu_{0,1,T}(t)$ is:

$$\mu_0(t) = \sum_{i=0}^{t-1} i\frac{P(i)}{\omega_0}$$

$$\mu_1(t) = \sum_{i=t}^{L-1} i\frac{P(i)}{\omega_1}$$

$$\mu_T = \sum_{i=0}^{L-1} iP(i)$$

Optimizing this grey scale image may require a large computation for bi-level and multi-level thresholds. Many methods have been proposed in previews papers to solve the image thresholding problems.

Kapur's Method

In this paper, a conditional entropy method called Kapur's entropy method [14,15]. This Kapur's entropy was initially proposed in 1985 to segment the gray scale image by maximizing the entropy of histogram [23]. This method determines the optimal threshold values which maximizes the overall entropy by using a vector of image thresholds Th = {th_1, th_2,… th_{k-1}}. Therefore, the Kapur's entropy will be;

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

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

$$H_1^c=\sum_{j_1}^{th_1} \frac{Ph_j^c}{\omega_0^c} \ln\left(\frac{Ph_j^c}{\omega_0^c}\right),$$
$$H_2^c=\sum_{j=th_1+1}^{th_2} \frac{Ph_j^c}{\omega_1^c} \ln\left(\frac{Ph_j^c}{\omega_1^c}\right), \qquad (2)$$
$$H_3^c=\sum_{j=th_k+1}^{L} \frac{Ph_j^c}{\omega_{k-1}^c} \ln\left(\frac{Ph_j^c}{\omega_{k-1}^c}\right)$$

is developed by imitating the blinking illumination patterns generated by fireflies, at an essence of its creation.

WherePh_j^c - the probability distribution of the intensity levels andω_0^c,ω_1^c, …., ω_{k-1}^c- probability occurrence for k levels, C is unity (1) for gray level images. The Firefly Algorithm (FA) based arbitrary work adjusts the threshold value of image until it reaches a J_{max} value.

Firefly Algorithm

Firefly Algorithm (FA) was first proposed by Yang [19-21]. This algorithm is nature-inspired meta-heuristic algorithm, which developed by blinking illumination pattern generated by fireflies. The Firefly Algorithm FA is developed by considering the following condition;

1) Fireflies are unisex which means one firefly will be attracted by another firefly of its sex which is nearer to the one.
2) The Attractiveness between the two fireflies is proportional to blinking luminance.
3) The brightness of a firefly is related with the cost function or fitness of firefly which is used for the searching process

During the searching process, the attracted firefly x towards the brighter firefly y can be determined by their respective position [15,18]. The updated position equation is:

$$X_x^{t+1}=X_x^t+\beta_0 e^{-\gamma d_{xy}^2}\left(X_y^t - X_x^t\right)+a_1 .\ sign\left(rand-\frac{1}{2}\right)+B(s)$$

Where X_x^{t+1} – Updated position of firefly, X_x^t – Initial position of firefly, $\beta_0 e^{-\gamma d_{xy}^2}\left(X_y^t - X_x^t\right)$ – the attractive force between fireflies, $B(s)=A.|s|^{a/2}$ – Brownian walk strategy, A is random variable, β is the spatial exponent and α is the temporal exponent.

The Three random parameters such as Brownian search based FA, Levy flight [20] based FA and traditional FA which are used to update the firefly position. All parameters of this algorithm has assigned already in recently proposed paper. In this paper, we presented a comparative analysis between Otsu's and Kapur's entropy function.

Implementation of Segmentation

The test image of Gray scale thresholding used to finds the threshold value within the range [0, L-1] by increasing the entropy value of histogram [25]. Similarly, the heuristic algorithm is used to determine the optimal threshold (Th) value for the test images in the threshold data space [0, L-1][3]. The dimension of segmentation [21-24] problem mainly depends on the m level. In this work, for the gray scale image segmentation problem, heuristic algorithms are allowed to find the optimal threshold levels (m).

During the segmentation process, Firefly algorithm is allowed to enquire the gray histogram [24] to find the threshold value. The process may continue till it attains the J_{max} value. The mean value is taken as an optimal value.

The quality measure of the segmented image is determined with the help of image metrics, such as Root Mean Square Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Matrix (SSIM). The PSNR gives similarity of segmented image against the original image based on the mean square error. The SSIM is used to generate the superiority of image and inter-dependency between original image and the extracted images.

Results and Discussion

Grey scale histogram based image segmentation experiment is implemented in Matlab R2010a software on an AMD C70 Dual Core 1GHz CPU, 4 GB RAM running with windows 8. The optimization is done on the parameter of firefly algorithm such as image size, threshold value, number of iterative function is fixed as 500, maximized objective function (J_{max}). The procedure is repeated 30times till it reaches the threshold value. This Firefly Algorithm (FA) approach is proposed to guide the multi-level thresholding process such as Otsu's and Kapur's entropy function for a threshold level Th={2,3,4,5}. The dimension of test image 512 x 512 pixel sized Gray level images are used for segmentation such as Mandrill, Traffic, Jet, Hunter.

Table 1 depicts the test images and corresponding grey scale histogram is shown. Table 2 depicts the segmentation process by extracted images for Otsu's function. The same procedure is repeated for image using FA and Kapur entropy function for *Th* = {2, 3, 4, 5} and the results for kapur's function are presented in table 2 and table 4. From table 3 and table 4, we can observe that NAE, NCC, PSNR, SSIM, RMSE are obtained with the firefly algorithm. From the table 3 and table 4, we found that Otsu's function is better than Kapur's entropy function. To analyse the statistical significance of the firefly algorithm [15,24], the related results are obtained in eachtrials. Table 5 illustrates the comparative analysis of PSNR, RMSE, SSIM between Otsu's function and Kapur function.

Table 1. Test image and their histogram

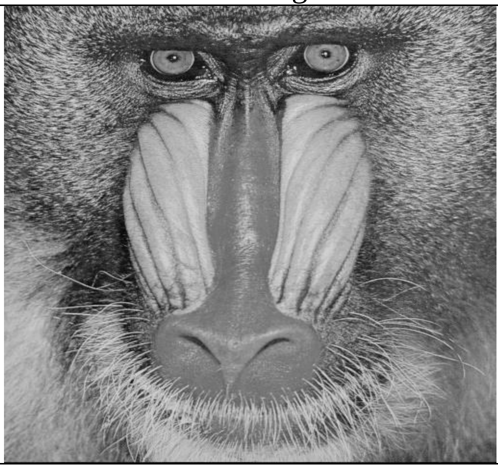
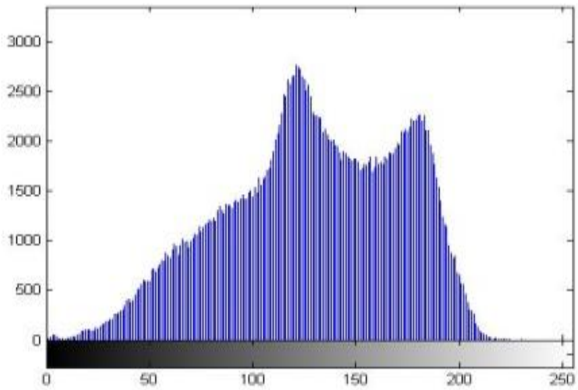
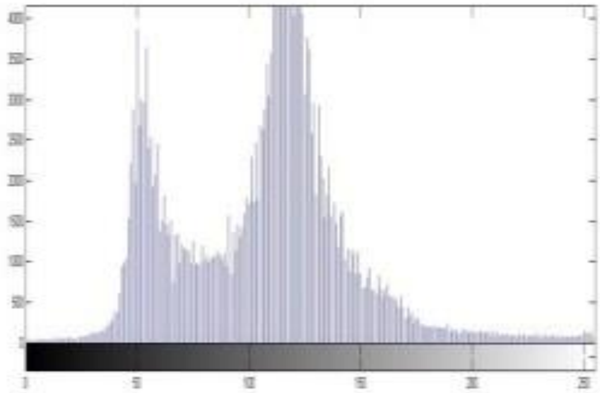
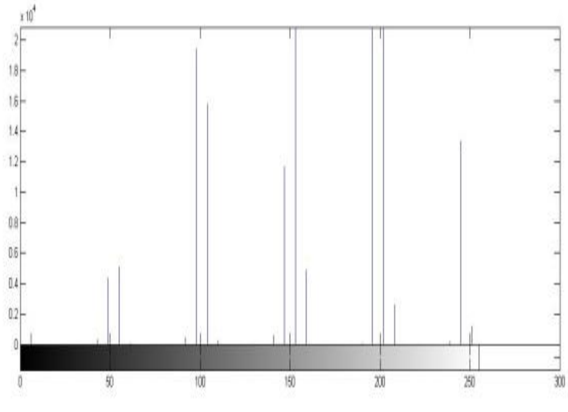
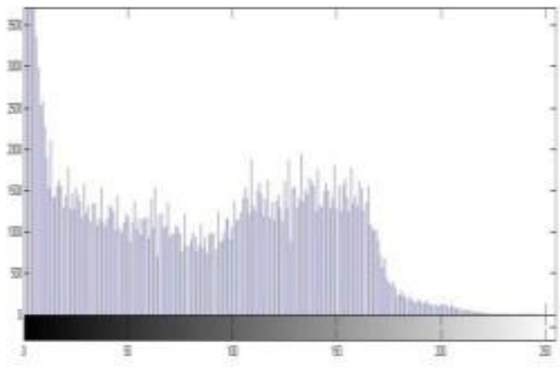
	Test Image	Gray scale histogram image
Mandrill		
Traffic		
Jet		
Hunter		

Table 2. Segmented image for Th = 2 to5

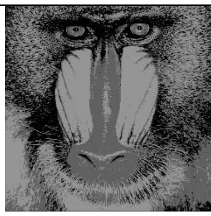
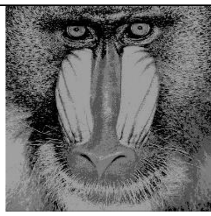
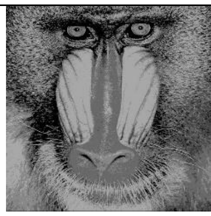
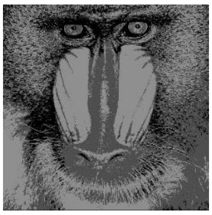
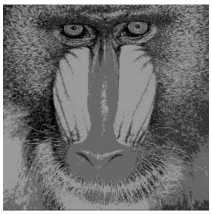
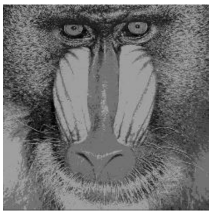
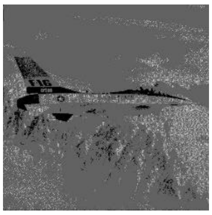
		Level 2	Level 3	Level 4	Level 5
Mandrill	Otsu				
	Kapur				
Traffic	Otsu				
	Kapur				
Jet	Otsu				
	Kapur				
Hunter	Otsu				
	Kapur				

Table 3. Performance measures with Otsu's threshold based segmentation

	Level	Optimal Threshold	NAE	RMSE	PSNR(dB)	NCC	SSIM
Mandrill	2	128	0.4733	70.9892	11.1070	0.5965	0.4876
	3	97,149	0.2750	42.4017	15.5831	0.7730	0.7389
	4	85,124,160	0.2041	32.6979	17.8404	0.8378	0.8117
	5	72,106,137,168	0.1553	24.9432	20.1918	0.8764	0.8804
Traffic	2	97	0.3940	50.9377	13.9900	0.6409	0.4692
	3	90,154	0.3586	43.8841	15.2847	0.6953	0.6331
	4	86,130,185	0.3187	39.4055	16.2197	0.7448	0.6803
	5	74,104,138,192	0.2325	31.3380	20.2094	0.8221	0.7544
Jet	2	154	0.2111	44.8040	15.1045	0.8061	0.6837
	3	116,174	0.2131	44.8020	15.2045	0.8261	0.6837
	4	95,146,191	0.1206	30.3729	18.4811	0.9029	0.7390
	5	87,130,172,202	0.1013	25.7190	19.9257	0.9295	0.7479
Hunter	2	80	0.3309	32.3192	17.9421	0.7041	0.6115
	3	51,116	0.3109	32.3172	17.9821	0.7161	0.6115
	4	36,86,135	0.2525	24.5269	20.3379	0.7927	0.7226
	5	27,65,104,143	0.2038	19.9311	22.1402	0.8353	0.7847

Table 4. Performance measures with kapur's entropy based segmentation

	Level	Optimal Threshold	NAE	RMSE	PSNR(dB)	NCC	SSIM
Mandrill	2	108	0.4050	59.7501	12.6040	0.6272	0.5466
	3	79 143	0.2745	40.2380	16.0381	0.7573	0.7640
	4	44 98 152	0.1994	29.5905	18.7078	0.8199	0.8447
	5	33 74 114 159	0.1654	24.8628	20.2198	0.8495	0.8730
Traffic	2	174	0.9151	104.206	7.7729	0.1407	0.0925
	3	99 174	0.3617	45.9649	14.8823	0.6997	0.5873
	4	95 143 190	0.2401	31.1266	18.2682	0.7681	0.7673
	5	40 98 143 192	0.2113	26.5671	19.6439	0.8066	0.8259
Jet	2	160	0.3852	79.0937	10.1680	0.6656	0.5305
	3	161 179	0.4335	84.6285	9.5805	0.5602	0.5157
	4	7 43 160	0.3390	65.1404	11.8538	0.6830	0.6116
	5	7 43 111 141	0.3116	59.5567	12.6322	0.6907	0.6698
Hunter	2	99	0.4681	45.5714	14.9569	0.6052	0.4141
	3	88 176	0.4530	43.6737	15.3264	0.6206	0.4508
	4	59 117 179	0.3138	30.1390	18.5482	0.7458	0.6184
	5	44 89 133 179	0.2356	22.3821	21.1328	0.8190	0.7154

Table 5. Comparative analysis of Otsu and Kapur

IMAGES	OTSU PSNR	KAPUR PSNR	OTSU RMSE	KAPUR RMSE	OTSU SSIM	KAPUR SSIM
MANDRIL2	11.1017	12.6041	40.9892	59.7501	0.6576	0.5466
MANDRIL3	17.5831	16.0381	32.4017	40.238	0.7389	0.5764
MANDRIL4	19.8404	18.7078	22.6979	29.5905	0.8117	0.8447
MANDRIL5	22.1918	20.2198	20.9432	25.8628	0.8804	0.7873
TRAFFIC 2	13.9219	17.1291	50.9377	72.2016	0.4692	0.3925
TRAFFIC 3	15.2847	14.8823	43.8841	45.9649	0.6331	0.5873
TRAFFIC 4	16.2197	18.2682	29.4055	31.1266	0.7803	0.6673
TRAFFIC 5	20.2094	19.6439	21.1338	26.5671	0.8544	0.8259
JET 2	15.1045	10.1618	44.8104	79.0937	0.6837	0.5305
JET3	16.3258	11.5805	50.2365	84.6285	0.6837	0.5157
JET4	18.4811	11.8538	30.3729	65.1404	0.739	0.6116
JET 5	19.9257	12.6322	50.2365	59.5567	0.7479	0.6698
HUNTER 2	16.9421	14.9569	32.3172	45.5714	0.6115	0.4141
HUNTER 3	17.2569	15.3264	40.2356	43.6737	0.6115	0.4508
HUNTER 4	20.3379	18.5482	24.5269	30.1391	0.7226	0.6184
HUNTER 5	22.1402	21.1328	19.9311	22.3821	0.7847	0.7154

Conclusions

In the present paper, multi-level thresholding image segmentation technique based on gray scale histogram image using Firefly Algorithm and Otsu's / Kapur's function. This method finds the optimal thresholds for the tested image based on the Th value by maximizing Jmax. The segmentation process is validated using an otsu's and Kapur's function for both qualitative and quantitative analysis of image segmentation, includes the performance measurement, such as Objective function, NAE, RMSE, PSNR, NCC and SSIM. The simulation result proved that the Otsu's thresholding is better than the kapur's function. An Otsu thresholding gives a better PSNR value than the kapur's function and RMSE value of thresholded image is reduced more in Kapur's function than the Otsu's method.

Conflict of interest

Authors declare there are no conflicts of interest.

References

[1] Pal NR, Pal SK. A review on image segmentation techniques. Pattern Recognition, 1993;26(9):1277-1294.

[2] Sezgin M, Sankar B. Survey over image thresholding techniques and quantitative performance evaluation. Journal of Electronic Imaging. 2004;13(1):146–65.

[3] Tuba M. Multilevel image thresholding by nature-inspired algorithms: A short review. Computer Science Journal of Moldova. 2014;22(3):318–38.

[4] Manikantan K, Arun BV, Yaradonic DKS. Optimal Multilevel Thresholds based on Tsallis Entropy Method using Golden Ratio Particle Swarm Optimization for Improved Image Segmentation. Procedia Engineering. 2012;30:364 – 371.

[5] Akay B.A study on particle swarm optimization and artificial bee colony algorithms for multilevel thresholding. Applied Soft Computing. 2013;13(6):3066–3091.

[6] Sri Madhava Raja, N; Rajinikanth, V; and Latha, K. Otsu Based Optimal Multilevel Image Thresholding Using Firefly Algorithm. Modelling and Simulation in Engineering. 2014;Article ID:794574.

[7] Sarkar S, Das S. Multilevel image thresholding based on 2D histogram and maximum Tsallis entropy – A Differential Evolution Approach. IEEE Transactions on Image Processing. 2013;22(12):4788-4797.

[8] Rajinikanth V, Couceiro MS. RGB Histogram based coolor image segmentation using firefly algorithm.

Procedia Computer Science. 2015;46:1449-1457.

[9] Martin D, Fowlkes C, Tal D, Malik J. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. Proceedings of the 8th International Conference on Computer Vision. Vancouver, BC. 2001;2:416–423.

[10] Lee SU, Chung SY, Park RHA. Comparative Performance Study Techniques for Segmentation, Computer Vision, Graphics and Image Processing. 1990;52(2):171-190.

[11] Raja NSM, Suresh Manic K, Rajinikanth V. Firefly algorithm with various randomization parameters: an analysis. Lecture Notes in Computer Science. 2013;8297:110-121.

[12] Otsu NA. Threshold selection method from Gray-Level Histograms, IEEE Transactions on Systems, Man and Cybernetics. 1979;9(1):62-66.

[13] Rajinikanth V, Sri Madhava Raja N, Satapathy SC. Robust Color Image Multi-thresholding Using Between-Class Variance and Cuckoo Search Algorithm. Advances in Intelligent Systems and Computing. 2016;433:379-386.

[14] Bhandari AK, Kumar A, Singh GK (2015) Modified artificial beecolony based computationally efficient multilevel thresholdingfor satellite image segmentation using Kapur's, Otsu and Tsallisfunctions. Expert Syst Appl 42(3):1573-1601.

[15] Suresh Manic K, Krishna Priya R and Rajinikanth V. Image Multithresholding Based on Kapur/Tsallis Entropy and Firefly Algorithm, Comparative analysis between Kapur/Tsallis. Indian Journal of Science and Technology. 2016;9(12):1-6.

[16] Krishnan PT, Balasubramanian P, Krishnan C. Segmentation of brain regions by integrating meta heuristic multilevel threshold with markov random field. Current Medical Imaging Reviews. 2016;12(1):4–12.

[17] Rajinikanth V, Sri Madhava Raja N, Latha K. Optimal Multilevel Image Thresholding: An Analysis with PSO and BFO Algorithms. Aust J Basic Appl Sci. 2014;8(9):443-454.

[18] Oliva D, Cuevas E, Pajares G, Zaldivar D, Osuna V.A Multilevel Thresholding algorithm using electromagnetism optimization. Neurocomputing. 2014;139:357-381.

[19] Yang XS. Firefly algorithms formultimodal optimization. Lecture Notes in Computer Science. 2009;5792:169–178.

[20] Yang XS. Firefly algorithm, Levy flights and global optimization. Research and Development in intelligent Systems. London: Springer-Verlag;2009.p.209-218.

[21] Sathya PD, Kayalvizhi R. PSO-based Tsallis Thresholding Selection Procedure for Image Segmentation. International Journal of Computer Applications. 2010;5(4):39–46.

[22] Wang Z, Bovik AC, Sheikh HR, Simoncelli EP. Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing. 2004;13(4):600-601

[23] Agrawal S, Panda R, Bhuyan S, Panigrahi BK. Tsallis entropy based optimal multilevel thresholding using cuckoo search algorithm. Swarm and Evolutionary Computation. 2013;11:16-30.

[24] Pun T.A new method for gray-level picture thresholding using the entropy of the histogram. Signal Process. 1980; 2(3):223-237.

[25] Oliva D, Cuevas E, Pajares G, Zaldivar D, Perez-Cisneros M. Multilevel Thresholding Segmentation Based on Harmony Search Optimization. Journal of Applied Mathematics, 2013;Article ID: 575414.

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