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Image Multithresholding based on Kapur/Tsallis Entropy and Firefly Algorithm

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Abstract

Background/Objectives: In this paper, Firefly Algorithm (FA) based multilevel thresholding is proposed to segment the gray scale image by maximizing the entropy value. **Methods/Statistical analysis:** Better segmentation method gives appropriate threshold values to enhance the region of interest in the digital image. The entropy based methods, such as Kapur's and Tsallis functions are chosen in this paper to segment the image. This work is implemented using the gray scale images obtained from Berkeley segmentation dataset. The FA assisted segmentation with entropy function is confirmed using the universal image superiority measures existing in the literature. **Findings:** Results of this simulation work show that Tsallis function offers better performance measure values, whereas the Kapur's approach offers earlier convergence with comparatively lower CPU time. **Applications/Improvements:** Proposed method can be tested using other recent heuristic methods existing in the literature.

Keywords: Entropy Value, Gray Scale Image, Kapur's Function, Multithresholding, Tsallis Function

1. Introduction

In the field of image processing, image segmentation is widely used to extract the section of interest in a digital image frame. It is an initial step in image processing, which helps in separating an image into non-overlapping, homogenous sections enclosing interrelated objects. Imaging literature provides the information about a number of segmentation procedures proposed and implemented by most of the researchers[1-3].

In general, image thresholding procedure is categorised as local level threshold and global level threshold. In the local level thresholding, various threshold values are allocate for every portion of the image, while in global level thresholding, a single threshold value is assigned to the whole image. During this process, a probability density function of the grey level histogram is used to find the threshold value with the help of parametric or a nonparametric approach[4].

Image thresholding based on the parametric approach is complex and time consuming. The final outcome by this procedure also affected due to the image quality and initial conditions. Hence, non-parametric approaches are widely adopted by most of the researchers to solve gray and colour image segmentation problem[5-8].

In this paper, image multi thresholding is proposed using a non-parametric approach, such as maximal entropy criterion.

During image multithresholding process, an essential threshold level (Th) is preset by the user with the help of an available signal processing scheme, which split the image in to various clusters. Locating the optimal threshold based on a chosen Th becomes a complicated task in traditional multi-level thresholding process. Hence, recent multi-level thresholding works are performed using heuristic algorithms, due to its reduced computation cost[3].

In this paper, Firefly Algorithm (FA) based approach is proposed to guide the multi-level thresholding process using Kapur's/Tsallis entropy function for a chosen threshold level $Th = \{2, 3, 4, 5\}$. The segmentation process is tested on 481×321 sized gray level images, such

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as Jet, Train, Flower and Snake existing in the Berkeley segmentation dataset[9]. The aim of the paper is to provide a comparative analysis between the Kapur's and Tsallis function using FA. The simulation work is implemented using Matlab R2010a and the image performance measures, such as Normalized Absolute Error (NAE), Root Mean Squared Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), Normalized Cross Correlation (NCC), Structural Similarity Index Matrix (SSIM) and the run time of CPU.

2. Related Previous Works

Due to its superiority, entropy based approaches are widely adopted by the research in the field of image multithresholding. Even though a number of entropy schemes are available, Kapur and Tsallis are used by the most of the researchers[3]. Heuristic algorithm and Kapur's technique is considered to find multilevel thresholds for clear and noise stained images in[10,11]. Artificial bee colony based satellite image multilevel thresholding along with Kapur's, Otsu's and Tsallis function is discussed in[12]. The above said work clearly presents the detailed comparative analysis between the between class variance function and entropy function.

Multi-level thresholding based on Tsallis entropy and cuckoo search for the segmentation of gray scale image is discussed in[13]. Bacterial foraging algorithm based approach is presented in[14] and Particle swarm optimization assisted Tsallis entropy based segmentation is discussed in[15-17]. Image segmentation with Fuzzy – Tsallis entropy and Shannon entropy based approaches are presented in[18,19].

3. Entropy based Segmentation

In image processing literature, variety of scheme is existing to perform the multi-thresholding process[1,20,21]. In this paper, a comparative analysis is presented between the most popular entropy schemes, such as Kapur and Tsallis function based on firefly algorithm and gray scale images. In entropy based approach, the segmentation process finds the optimal threshold, which maximizes the overall entropy.

3.1 Kapur's Function

Kapur's entropy function was originally proposed in 1985 to segment the gray scale image by maximizing the entropy of histogram [22]. In order to get the threshold using Kapur's method; let, Th = $[th_1, th_2, ..., th_{k-1}]$ is a vector of the image thresholds.

Then, the Kapur's entropy will be;

$$J_{max} = f_{kapur}(Th) = \sum_{j=1}^{k} H_j^C \tag{1}$$

Generally, each entropy is computed independently based on the particular *th* value.

For multi-level thresholding problem, it can be expressed as;

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

where Ph_j^C is the probability distribution of the intensity levels, C is unity (1) for gray level images and $w_0^C, w_1^C, ... w_{k-1}^C$ probability occurrence for k levels. The FA based search arbitrarily adjusts the values of threshold until J_{max} is reached.

3.2 Tsallis Function

Non-extensive entropy concept of Tsallis was originally derived from Shannon's theory[23] and it can be defined as;

$$S_q = \frac{1-\sum_{j=1}^{Th}(p_j)^q}{q-1} \tag{3}$$

where T is the system potentials and q is the entropic index. The above equation satisfies Shannon's entropy when $q \rightarrow 1$.

The pseudo additivity rule for the entropy can be expressed as follows;

Let the gray scale image has L gray levels in the range {0,1, ..., L-1}, with probability distributions $p_i = p_0, p_1, ..., p_{L-1}$.

Then, Tsallis multi thresholding can then be expressed as:

$$\begin{aligned} J_{max} = f(Th) = [Th_1, Th_2, \ldots, Th_k] = argmax[S_q^A(Th) + S_q^B(Th) \\ + \ldots + S_q^K(Th) + (1-q).S_q^A(Th).S_q^B(T)\ldots S_q^K(Th)] \end{aligned} \tag{4}$$

where

$$S_q^A(Th) = \frac{1 - \sum_{j=0}^{t_1-1}\left(\frac{Pj}{P^A}\right)^q}{q-1}, P^A = \sum_{j=0}^{t_1-1} Pj$$

$$S_q^B(Th) = \frac{1 - \sum_{j=t_1}^{t_2-1}\left(\frac{Pj}{P^B}\right)^q}{q-1}, P^B = \sum_{j=t_1}^{t_2-1} Pj \tag{5}$$

$$S_q^K(Th) = \frac{1 - \sum_{j=t_k}^{L-1}\left(\frac{Pj}{P^K}\right)^q}{q-1}, P^K = \sum_{j=t_k}^{L_2-1} Pj$$

are subject to the following constraints:

$$\left|P^A + P^B\right| - 1 < S < 1 - \left|P^A - P^B\right|$$

$$\left|P^B + P^C\right| - 1 < S < 1 - \left|P^B - P^C\right| \tag{6}$$

$$\left|P^K + P^{L-1}\right| - 1 < S < 1 - \left|P^K - P^{L-1}\right|$$

During the multi thresholding practice, the optimal threshold value *Th* which maximizes *f (Th)*. In this work, the threshold values are chosen as *Th* = {2, 3, 4, 5}, thus the required probability values are P^A, P^B, P^C, P^D and P^E. The FA based search randomly alters the values of threshold until J_{max} is reached.

4. Firefly Algorithm

Firefly Algorithm (FA) was initially proposed by Yang[24,25]. It is a nature-inspired algorithm, developed by imitating the blinking illumination patterns generated by fireflies. Detailed description about FA can be found in[6,26,27].

During the search process, the movement of an attracted firefly *x* towards a brighter firefly *y* can be determined by the following position update equation:

$$X_x^{t+1} = X_x^t + \beta_0 e^{-\gamma d_{xy}^2}(X_y^t - X_x^t) + \alpha_1 .\ sign\ (rand\ \text{-}\ 1/2) \oplus\ B(s) \tag{7}$$

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

All algorithm parameters are assigned based on the recent image segmentation papers[6,7]. The advantage of FA in the field of image multithresholding already exists in the literature. Hence, in this work we presented only the comparative analysis between Kapur and Tsallis function.

Implementation of the segmentation is as follows:

The multithresholding problem of gray scale image finds the best possible thresholds within the range [0, L-1] by maximizing the entropy of histogram.

The FA and Kapur/Tsallis approach is considered to find the optimal threshold in the *Th* dimensional search space. During the segmentation procedure, FA is allowed to investigate the gray histogram to find the *Th* till the J_{max} is reached. The search process is repeated 30 times and the mean value is chosen as the optimal value in the case of Kapur and Tsallis.

The quality of the segmented image is then computed with the help of image metrics, such as Normalized Absolute Error (NAE), Root Mean Squared Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), Normalized Cross Correlation (NCC)[28], Structural Similarity Index Matrix (SSIM)[29] and the run time taken by the CPU.

5. Results and Discussion

Firefly algorithm supervised Kapur/Tsallis 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 FA parameters: population size is 25, dimension of search is *Th* (chosen threshold), maximum number of iteration is fixed as 500 and maximized objective function (J_{max}) is the guideline to terminate the search process. This procedure is repeated 30 times on each image using Kapur and Tsallis function and the mean value of threshold is recorded as the optimal threshold.

Table 1 depicts the test images and corresponding histograms. Initially the proposed multi-level segmentation process is applied on Jet image using FA and Kapur for *Th* = {2, 3, 4, 5}. The thresholded images are depicted in Table 2 and the related threshold values and image quality measures are shown in Table III. Same procedure is repeated on the considered image dataset using FA and Tsallis function for *Th* = {2, 3, 4, 5} and the results are presented in Table 2 and Table 4.

From Table 3 and Table 4, one can observe that, NAE, RMSE, PSNR, NCC and SSIM obtained with the FA guided Kapur is better compared with Tsallis. But, the

Tsallis approach offered better CPU time for all the cased compared with the alternative.

In order to analyse the statistical significance of the proposed method, all the related results obtained during the 30 trials are considered. These results are then

Table 1. Test images and the gray scale histogram

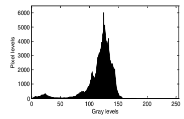
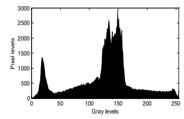
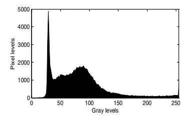
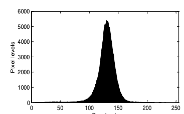
	Image	Histogram
Jet		
Train		
Flower		
Snake		

Table 2. Segmented images for Th = 2 to 5

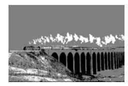
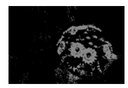
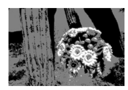
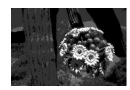
		Th = 2	Th = 3	Th = 4	Th = 5
Jet	*Kapur*				
	Tsallis				
Train	*Kapur*				
	Tsallis				
Flower	*Kapur*				
	Tsallis				
Snake	*Kapur*				
	Tsallis				

Table 3. Performance measures with Kapur's Entropy based segmentation

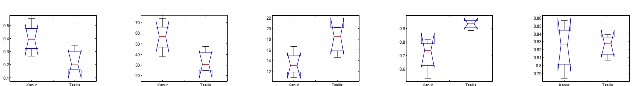
	Th	OT	NAE	RMSE	PSNR(dB)	NCC	SSIM	CPU time (s)
Jet	2	72,116	0.3491	43.7022	15.3207	0.6504	0.7287	9.1973
	3	63,105,129	0.3362	42.2652	15.6111	0.6643	0.7309	11.0381
	4	60,86,117,148	0.2085	27.0564	19.4854	0.7921	0.8032	19.7929
	5	52,81,126,166,182	0.1492	20.0464	22.0901	0.8555	0.8111	22.4816
Train	2	69,121	0.7884	111.5823	7.1789	0.2844	0.6896	11.3294
	3	62,98,137	0.3072	44.9545	15.0753	0.7300	0.7223	17.1037
	4	54,84,126,178	0.2086	31.1636	18.2579	0.8092	0.8138	25.2209
	5	50,76,122,163,190	0.1876	27.9159	19.2138	0.8437	0.8592	27.3244
Flower	2	74,122	0.8261	75.5670	10.5642	0.2942	0.7272	10.8846
	3	66,108,142	0.7074	65.7159	11.7774	0.4436	0.7580	16.2209
	4	59,84,134,178	0.4201	40.6389	15.9520	0.6956	0.8087	17.8247
	5	52,78,131,159,192	0.3630	34.8687	17.2821	0.7460	0.8158	19.1184
Snake	2	68,120	0.3873	51.8836	13.8302	0.6115	0.7774	10.2935
	3	58,106,144	0.3109	42.4147	15.5805	0.6857	0.7982	13.1183
	4	49,86,115,162	0.3055	41.6090	15.7471	0.6932	0.8058	18.0792
	5	46,94,124,170,196	0.1860	26.3686	19.7090	0.8109	0.8127	22.8630

Table 4. Performance measures with Tsallis Entropy based segmentation

	Th	OT	NAE	RMSE	PSNR (dB)	NCC	SSIM	CPU time (s)
Jet	2	105,188	0.6355	82.0843	9.8456	1.6385	0.7964	11.3085
	3	72,139,194	0.6280	76.0532	10.5085	1.6122	0.8193	16.2874
	4	66,117,175,218	0.5359	65.3366	11.8277	1.5175	0.8216	17.9527
	5	57,88,126,196,234	0.1823	37.3913	16.6754	1.1472	0.8498	21.9473
Train	2	108,163	0.3278	46.9071	14.7060	0.7490	0.7826	10.0057
	3	83,124,196	0.1816	28.7798	18.9490	0.9398	0.8016	14.2084
	4	64,122,182,205	0.1707	26.8638	19.5475	0.8992	0.8272	19.2927
	5	55,82,133,171,228	0.1167	17.9631	23.0432	1.0179	0.8392	21.2746
Flower	2	113,174	0.4452	41.0239	15.8701	1.1492	0.8064	15.3217
	3	86,126,203	0.3661	33.9248	17.5204	0.7532	0.8187	18.2324
	4	74,131,186,226	0.3043	30.7111	18.3849	0.9079	0.8226	21.4858
	5	65,91,140,178,240	0.2958	28.8644	18.9235	0.8357	0.8350	26.2207
Snake	2	116,172	0.2951	44.0581	15.2503	1.2921	0.8081	15.1219
	3	102,155,198	0.3019	41.1402	15.8455	1.2887	0.8126	18.3185
	4	84,122,191,220	0.1247	18.5854	22.7474	1.0524	0.8279	24.0064
	5	76,92,137,188,241	0.0846	14.9619	24.6311	0.9722	0.8402	25.1875

Table 5. Anova test results

Kapur		Tsallis	
Parameters	*P-value*	Parameters	*P-value*
NAE	<0.0104	NAE	<0.0208
RMSE	<0.0381	RMSE	<0.0265
PSNR	<0.0273	PSNR	<0.0134
NCC	<0.0252	NCC	<0.0222
SSIM	<0.0198	SSIM	<0.0236



(a) NAE **(b) RMSE** **(c) PSNR** **(d) NCC** **(e) SSIM**

Figure 1. Overall performance measure with ANOVA test.

analysed using the Kruskal–Wallis ANOVA test[30]. The smaller p-value confirms that the particular parameter is statistically significant. From the ANOVA test (Figure 1 and Table 5), it is observed that, for most of the quality measures, Tsallis based approach is statistically more significant than Kapur's function.

6. Conclusion

In this work, image multi thresholding is presented for gray scale image dataset using FA and Kapur/Tsallis function. This process discovers optimal thresholds for the test image based on the chosen *Th* value by maximizing J_{max}. The performance of this method is confirmed using the image superiority measures, such as NAE, RMSE, PSNR, NCC and SSIM. The average CPU time taken to complete the thresholding process is also recorded. This simulation result evident that, Kapur's approach offers better image quality measures and Tsallis function provides the reduced CPU time. The statistical significance test also proves that, Tsallis approach is statistically significant compared with Kapur.

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