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A Multilevel Image Thresholding Based on Hybrid Jaya Algorithm and Simulated Annealing

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ABSTRACT

Thresholding is a method for region-based image segmentation, which is important in image processing applications such as object recognition Multilevel. Thresholding is used to find multiple threshold values. Image segmentation plays a significant role in image analysis and pattern recognition. While threshold techniques traditionally are quite well for bi-level thresholding algorithms, multilevel thresholding for color images may have too much processing complexity. Swarm intelligence methods are frequently employed to minimize the complexity of constrained optimization problems applicable to multilevel thresholding and segmentation of color (RGB) images; In this paper, the hybrid Jaya algorithm with the SA algorithm was proposed to solve the problem of computational complexity in multilevel thresholding. This work uses Otsu method, Kapur entropy and Tsallis method as techniques to find optimal values of thresholds at different levels of color images as the target Tasks Experiments were performed on 5 standardized color images and 3 grayscale images as far as optimal threshold values are concerned, Statistical methods were used to measure the performance of the threshold methods and to select the better threshold, namely, PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error), SSIM (Structural Similarity Index), FSIM (Feature Similarity Index) and values of objective at many levels. The experimental results indicate that the presenter's Jaya and Simulated Annealing (JSA) method is better than other methods for segmenting color (RGB) images with multiple threshold levels. On the other hand, the Tsallis entropy of the cascade was found to be more robust and accurate in segmenting color images at multiple levels.

1. Introduction

One of the most crucial uses of metaheuristic algorithms is image segmentation. Segmenting an image is an essential part of image analysis and pattern recognition. Using image segmentation, a digital image can be divided into many sets of pixels. This can be useful for image processing, object representation, visualization, and image analysis activities used in various fields of applications; segmentation is a key first step.

Segmenting an image is the primary objective is to transform the relevant image sample into a simpler, more readily analyzed image.

Many image segmentation methods exist, such as Template matching, Hough transformation, Neural Networks and threshold[1].

One of the easiest and most popular techniques for segmenting images is histogram-based thresholding. The thresholding of histograms can be either single or level based[2].

It is possible to divide the image into two categories with a single threshold or into three or more classes with two or more thresholds [2]. Thresholding is used when

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separating foregrounds and backgrounds in an image [1].

Threshold with optimization algorithms Several modified optimization algorithms with multilevel thresholds have been used to improve the global performance of the threshold, and the image threshold values should be determined to find the best value. There are two kinds of optimization methods, global and local, and each contains a set of optimization algorithms .

This paper proposed a hybrid JSA algorithm to solve the problem of computational complexity in multi-level thresholding in which the complexity increases with increasing number of thresholds. Three thresholding methods were used to determine the optimal threshold value for image segmentation.

The main contribution of this paper is represented in the following:

- Apply haze removal techniques to pre-process images.
- It uses hybrid the basic Jaya algorithm with local search optimization algorithm can help it to get good result and not stuck in local optima as it helps it to escape from local optima, and evaluated it by benchmark functions.
- Application of the JSA algorithm to the M-L thresholding
- Using three thresholding methods (Otsu, Kapur, Tsallis) with JSA algorithm.
- The fitness value, peak signal-to-noise ratio (PSNR)[3], structure similarity index (SSIM)[4], feature similarity (FSIM)[5], Mean Square Error (MSE)[6], Fitness, execution time which means the computational time (CPU) will be used to evaluate the overall performance of JSA algorithm.

Finally, structure of this paper including introduction, literature work, the research methodology, the result from compression and discuss, and conclusions.

2. Literature Work

Due to its simplicity, the thresholding method is one of the most commonly used for segmenting images. It is used to differentiate an image's Background from its Foreground [1].

Simrandeep Singh et al.(2020) In a recent study, LebTLBO (Learning enthusiasm-based teaching and learning-based optimization) is an algorithm that is simple and computationally inexpensive and was developed for efficient, straightforward, and computationally inexpensive teaching and Learning. A key method for picture segmentation is multilevel thresholding (MT). In this study, Otsu and Kapur's method MT objective functions are merged with the search capacity of the algorithm to create LebTLBO, which is applied to ten common test photos with various histograms. The proposed methods for Otsu and Kapur's entropy approaches are compared with GA, MTEMO, PSO, and BF, the current state-of-the-art optimization methods. Regarding performance indicators, LebTLBO appears very effective in the trial[7].

Lifang He a and Songwei Huang.(2020) Used Kapur's entropy, Tsallis entropy, and Otsu's method as objective functions, an efficient krill herd algorithm (EKH) is proposed to search for optimal thresholding values. Experiments run on 10 color benchmark images on various levels; SSIM, PSNR, and standard deviation of objective values are the best thresholds. The experimental findings demonstrate the superiority of the provided compared to other color image thresholding algorithms, and the EKH algorithm does a better job segmenting color images. However, it is discovered that Kapur's method is more reliable and accurate for RGB image multilevel thresholding segmentation[8].

Ashish Kumar Bhandari. (2020) A fresh, fast RGB image multilevel thresholding method based on beta differential evolution (BDE) with two objective functions has been introduced. Combining the BDE algorithm with the thresholding functions that maximize Tsallis and Kapur's entropy determines a threshold value that is optimal. Five real-world true color photos and four satellite images are used to visually and computationally show the effectiveness of the proposed methodology. Experimental results are presented in terms of the better objective function, threshold value, and computational cost for each approach at various thresholding levels. The superiority of quality is then thoroughly analyzed with relation to the suggested plan. The findings of the experimental evaluation demonstrate that the suggested method based on BDE for multilevel color (RGB) image segmentation may accurately and effectively search for numerous thresholds that are close to the ideal ones utilizing an exhaustive search process[9].

Zheping Yan et al.(2021) solved the image segmentation issue using optimization methods based on Kapur's entropy principle for WOA. Exploration and exploitation can be balanced well by the WOA aim to achieve the world's best solution by avoiding early convergence. To confirm the segmentation performance of the WOA, experiments were conducted in Harbin Engineering University's experimental pool to maximize Kapur's entropy value. The segmentation results are compared with those of the BA, the FPA, MFO, the MSA, PSO, and WWO. Each algorithm's overall performance is assessed using the fitness values, peak signal-to-noise ratio, structure similarity index, execution time, and Wilcoxon's rank-sum test. According to the experimental findings, the WOA outperforms the other comparative methods in terms of segmentation accuracy, segmentation effect, and robustness. WOA's viability and effectiveness are confirmed [10].

Shikai Wang et al.(2021) The ant lion optimizer uses opposition-based Learning to segment color images using multilevel thresholding. Segmentation is performed using Otsu and Kapur's entropy thresholding approach. They are employed as the objectives. The temporal complexity grows exponentially as the number of thresholds rises. Based on opposition-based Learning, a modified ant-lion optimizer algorithm (MALO) is suggested to resolve this issue by maximizing the objective functions to identify the ideal threshold values. A number of experiments fully demonstrate that the MALO is a powerful and effective thresholding technique due to its high search accuracy and convergence speed. It increases both search accuracy and convergence performance by using the opposition-based learning strategy [11]

Simrandeep Singh et al.(2021) Firefly Algorithm (FA) and Dragonfly Algorithm (DA) are combined in a new hybrid version. Complex multilayer threshold issues are solved for Image segmentation. A novel optimization technique called DA was proposed based on dragonflies' dynamic and static swarming behavior. The global search capability of DA is excellent with random and static swarm behavior, but the local search capability is constrained, leading to local options for trapping optima. The social behavior of fireflies, which includes producing lamps to entice potential mates, has an impact on the firefly method. The recommended method combines the firefly Algorithm's capacity to exploit and the ability to investigate DA to find the best possible global solutions. In this study, ten common test photos with varied histograms are subjected to HDAFAA comparison between the proposed methods for OTSU and Kapur's methods, as well as with recent benchmark optimization algorithms such as MTEMO, GA, PSO, and BF. Quantitative results show that HDAFA is highly efficient in terms of PSNR, mean, thresholds, iteration counts, and image segmentation quality [12].

Dongmei Wu and Chengzhi Yuan.(2022) proposed an image threshold segmentation method based on an improved sparrow search algorithm (ISSA)and 2-D maximum entropy method. In the proposed algorithm, the nonlinear inertia weight is introduced into the entrants' update formula to improve the local exploration ability of the algorithm, and Levy flight is introduced into the vigilant sparrows' update formula to prevent the algorithm from falling into the local optimal solution in the later stage of iteration. In addition, improved sparrow search algorithm is tested on fifteen benchmark functions. The proposed algorithm is applied to entropy based image segmentation. Experiment results on classical images and medical images show that the proposed method improves the segmentation effect in terms of peak signal-to-noise ratio and feature similarity [13].

The hybrid Jaya algorithm with the SA algorithm was proposed to solve the problem of computational complexity in multilevel thresholding. It distinguishes us from previous studies because the proposed algorithm was applied for the first time in the field of multilevel thresholding for image segmentation, and three limbs Otsu, Kapur, and Tsallis were used to determine the best threshold with the proposed algorithm for segmentation color and grayscale images. The performance of the proposed algorithm is evaluated by means of statistical measures (PSNR,SSIM,FSIM,MSE).

3. The Research Methodology

This diagram illustrates the work methodology, where the images used are processed using blur removal technology, and then the images are segmented using

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three threshold methods to determine the best thresholding for segmentation, then the solutions are evaluated and arranged from best to worst, and the solutions are updated using the JSA algorithm, evaluated, and choose the best threshold for image segmentation, show fig 1**:**

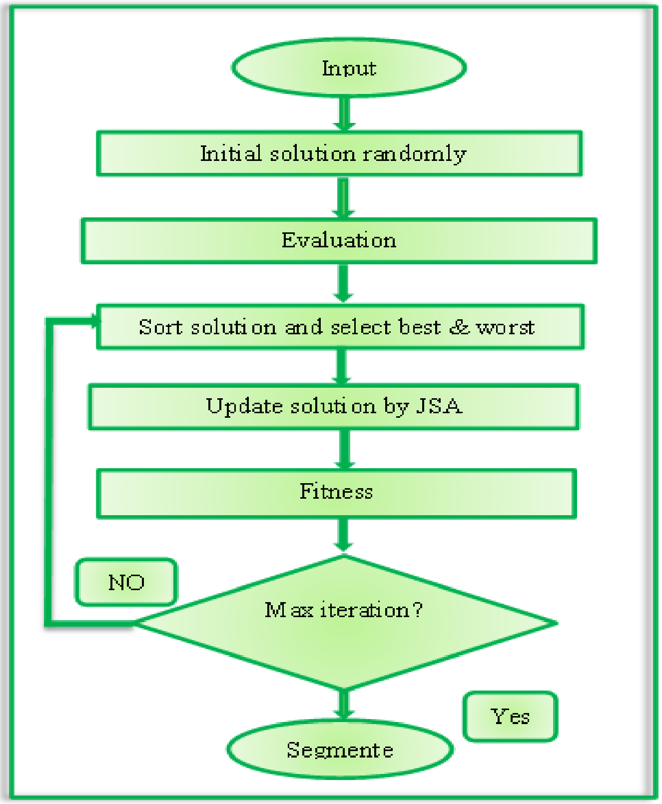

Fig 1: Conceptual framework of the research.

3.1Threshold Methods

The three threshold methods used are Otsu, Kapur and Tsallis, which are explained below.

3.1.1 Otsu Method

A non-parametric segmentation technique called the Otsu method (Between-class variance) divides the image into several classes [14]. The fundamental idea behind this method is to divide an image's pixels into two groups. By increasing the variance between the regions, Otsu's method attempts to separate the regions that include pixels with similar brightness[1].

Eq (1) describes interclass variance as a function [16].

$$\sigma_0^2 = \omega_0(\mu_0 + \mu_T)^2 . \sigma_1^2 = \omega_1(\mu_1 + \mu_T)^2 . \cdots . \sigma_m^2 = \omega_m(\mu_m + \mu_T)^2$$

Where $\mu_0 = \frac{\sum_{i=0}^{t_1-1} iP_i}{\omega_0} . \mu_1 = \frac{\sum_{i=t_1}^{t_2-1} iP_i}{\omega_1} . \cdots . \mu_m = \frac{\sum_{i=t_m}^{N-1} iP_i}{\omega_m}$ (1)

Where,

$\mu_0 . \mu_1 . \cdots\cdots . \mu_m$ = the mean intensity value of the pixel of class 0, 1, ⋯⋯, m respectively, for multilevel thresholding.

μ_T = global average.

P_i = probable pixel intensity value of i of 0 to 255

N = sum of different intensity levels.

So, to obtain the peak threshold values, the segmentation method hikes f(t), which shows the summation of the inter-class variance function.

$$\overrightarrow{t^*} = \arg\max\big(f(t)\big) \quad Where\ f(t) = \sum_{i=0}^{m} \sigma_i^2 \qquad (2)$$

Grayscale and RGB images can both be processed using this method.

As for the fonts and the sizes of the headings, this manuscript constitutes a good example.

3.1.2 Kapur Entropy Method

In 1985, Kapur proposed the maximum entropy method for precisely segmenting images. This technique operates by increasing the histogram of the image's entropy. This algorithm, created by Kapur for gray image segmentation, chooses the best threshold settings to maximize the entropy of the histogram. Intensity values for grayscale images range from Intensity I to [1,256][17]. Using this method, we can determine the ideal threshold value that will allow the total entropy to be increased. Entropy calculation basically determines the separability and compactness between each class in an image [18]. As an extension of Kapur's approach, we can formulate it as follows [19]:

$$f(t_1.t_2. \cdots\cdots . t_n) = H_0 + H_1 \cdots\cdots + H_n \qquad (3)$$

Where

$$H_0 = -\sum_{i=0}^{t_1-1} \frac{P_i}{\omega_0} \ln\frac{P_i}{\omega_0} . \qquad \omega_0 = \sum_{i=0}^{t_1-1} P_i$$

$$H_1 = -\sum_{i=t_1}^{t_2-1} \frac{P_i}{\omega_1} \ln\frac{P_i}{\omega_1} . \qquad \omega_1 = \sum_{i=t_1}^{t_2-1} P_i$$

$$H_2 = -\sum_{i=t_2}^{t_3-1} \frac{P_i}{\omega_2} \ln\frac{P_i}{\omega_2} . \qquad \omega_2 = \sum_{i=t_2}^{t_3-1} P_i$$

$$H_n = -\sum_{i=t_n}^{L-1} \frac{P_i}{\omega_n} \ln\frac{P_i}{\omega_n} . \qquad \omega_n = \sum_{i=t_n}^{L-1} P_i$$

The optima thresholds are found by maximizing the objective function, that is:

$$t^* = \quad \arg \quad \max(f(t_1 . t_2 . \cdots\cdots t_n)) \quad (4)$$
$$0 \le t \le L-1$$

where L is the total number of distinct intensity levels in the gray scale image and H0, H1,...Hn is the entropy value of the n + 1 different regions or classes. Pi is the chance that the pixel intensity value will be the value I where I range from 0 to 255. By processing the R, G, and B channels independently, it can be used for color image segmentation.

3.1.3 Tsallis Entropy Method

Shannon's entropy has been updated into Tsallis entropy. Shannon initially used entropy to estimate the system's ambiguous information content. Entropy is frequently used to assess the degree of disorder present in a system [20]. Tsallis has proposed generalizing Boltzmann-Gibbs (BGS) statistics on the basis of multi-fractal theory[7], and the expression can be described as:

$$S_q = \frac{1-\sum_{i=1}^{k}(p_i)^q}{q-1} \qquad (5)$$

Where p spans from 0 to 1 and indicates the likelihood that the modelled system will be in the state k is the total number of possible configurations for the system, q specifies the degree of non-extensivity.

Tsallis method of the system can be calculated by a pseudo additivity entropic rule using Eq(6)[2] [8]:

$$S(f_g^c + b_g^c) = S_q\,(f_g^c) + S_q\,(b_g^c) + (1-q).\, S_q\,(f_g^c).\, S_q\,(b_g^c)$$

$$C = \begin{cases} 1.2.3 & \textit{if} \quad RGB \quad image \\ 1 & \textit{if} \quad gray\ scale \quad image \end{cases}$$

(6)

Where,

f_g^c =Foreground of an image.

b_g^c =Background of an image.

Where the Foreground and Background of an image are indicated byf_g and b_g. You can segment grayscale and color images with this technique. Thus, the formulation for multilevel (m-level) image thresholding using the Tsallis entropy method is

$$S_q^{C_0}(t) = \frac{1-\sum_{i=0}^{t1-1}(P_i^C \,|P^{C_0}\,)^q}{q-1};$$

$$S_q^{C1}(t) = \frac{1-\sum_{i=t1}^{t2-1}(P_i^C \,|P^{C_1}\,)^q}{q-1} \quad ;$$

$$S_q^{C_m}(t) = \frac{1-\sum_{i=t_m}^{L-1}(P_i^C \,|P^{C_m}\,)^q}{q-1}$$

(7)

Where $P^{C_0} = \sum_{i=0}^{t-1} P_i^C$; $P^{C_1} = \sum_{i=t}^{t_2-1} P_i^C$; $P^{C_m} = \sum_{i=t_m}^{N-1} P_i^C$

Accommodating the optimal threshold values as:

$$\left[\overrightarrow{t_0^*}.\overrightarrow{t_1^*}.\overrightarrow{t_2^*}.\cdots.\overrightarrow{t_m^*}\right] = \arg\max(S_q^{C_0}(t) + S_q^{C_1}(t) + \cdots + S_q^{C_m}(t) + (1+q)\cdot S_q^{C_0}(t)\cdot S_q^{C_1}(t) \cdots S_q^{C_m}(t)) \qquad (8)$$

Subject to the following constraint:

$$|P^{C_0} + P^{C_1}| - 1 < S^{C_0} < 1 - |P^{C_0} + P^{C_1}|\,.\,|P^{C_1} + P^{C_2}| - 1 < S^{C_1} < 1 - |P^{C_1} + P^{C_2}\,| \,\&\, |P^{C_{m-1}} + P^{C_m}| - 1 < S^{C_{m-1}} < 1 - |P^{C_{m-1}} + P^{C_m}\,|$$

(9)

P^{C_0} , P^{C_1}, ... P^{C_m} can be formed from the probability distribution of pixel values corresponding to the threshold levels $\overrightarrow{t_0^*}.\overrightarrow{t_1^*}.\overrightarrow{t_2^*}.\cdots.\overrightarrow{t_m^*}$

4. The result from Compression and Discuss

In this section, we present the results of the proposed algorithm (JSA) and discuss them. It includes the results of three threshold methods: Otsu, Kapur and Tasalis. It is applied to color and grayscale images.

4.1 Otsu Method

The Otsu method was applied with the Hybrid Jaya algorithm with the Simulated Annealing algorithm(JSA) to choose the best threshold. Experiments were conducted on 8 images, including 5 color images and 3 known grey images. All images are of size (512 ×512)pixels. In this experiment, 10 threshold levels were used to segment the multilevel color image threshold. All experiments were repeated 20 times for each picture and each level. as shown in Table(1) below.

Table 1: Use The otsu Method

JSA

K	Image	Fmax	Time(S)	PSNR	MSE	SSIM	FSIM
	Im1	**3983.406**	**2.673**	**29.972**	**1.868**	**0.992**	**0.990**
	Im2	**7427.043**	**2.255**	**29.481**	**1.849**	**0.990**	**0.999**
	Im3	**7430.201**	**2.425**	**29.844**	**1.864**	**0.997**	**0.967**
10	**Im4**	**5559.682**	**2.156**	**29.592**	**1.870**	**0.996**	**0.981**
	Im5	**3191.933**	**2.142**	**30.532**	**1.868**	**0.993**	**0.995**
	Im6	**2652.210**	**1.884**	**29.482**	**1.824**	**0.994**	**0.999**
	Im7	**2652.647**	**1.582**	**29.471**	**1.821**	**0.996**	**0.984**
	Im8	**1679.596**	**2.287**	**29.302**	**1.855**	**0.999**	**0.965**

Relying on the results mentioned in table(1), it was found that the best threshold of 10 achieved the best results when applied in most of the images, depending on the value of the PSNR, where the threshold of 10 achieved the best PSNR in the image Im5. Also, SSIM, FSIM, and MSE were calculated for this image. As shown in Figure 2:

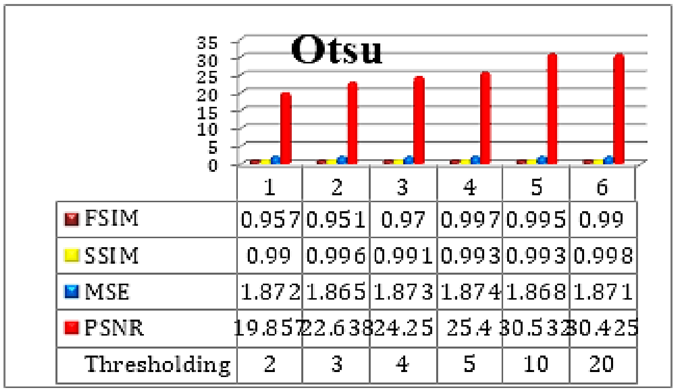

Fig 2: The Best Statistical Measurements for The Color Image in The Otsu Method

Figure (2) shows that after applying the JSA algorithm with setting the threshold coefficient of 10, got the best statistical measures which are 30.532, 1.868, 0.993, and 0.995 for PSNR, MSE, SSIM and FSIM, respectively.

4.2 Kapur Entropy Method

The Kapur method was applied with the Hybrid Jaya algorithm with the Simulated Annealing algorithm(JSA) to choose the best threshold. Experiments were conducted on 8 images, including 5 color images and 3 gray images. All images are size (512 ×512) pixels. To segment the multilevel color image threshold, the thresholds used in this experiment are 2, 3, 4, 5, 10 and 20 levels. All experiments were repeated 20 times for each image . as shown in Table(2):

Table 2: Use The Kapur Entropy Method.

				JSA			
K	Image	Fmax	Time(S)	PSNR	MSE	SSIM	FSIM
	Im1	51.230	4.757	33.060	1.863	0.996	0.996
	Im2	50.891	4.586	32.971	1.851	0.999	0.969
	Im3	50.642	6.717	32.477	1.870	0.991	0.958
20	Im4	51.577	6.700	32.784	1.872	0.993	0.994
	Im5	0	6.565	33.404	1.871	0.990	0.955
	Im6	51.501	6.033	32.660	1.832	0.999	0.994
	Im7	50.624	6.926	33.362	1.803	0.993	0.977
	Im8	0	6.645	32.474	1.864	0.999	0.983

Relying on the results mentioned in table(2), it was found that the best threshold of 20 achieved the best results when applied in most of the images, depending on the value of the PSNR, where the threshold of 20 achieved the best PSNR in the image Im5, and SSIM, FSIM, MSE and PSNR were also calculated. As shown in Figure 3:

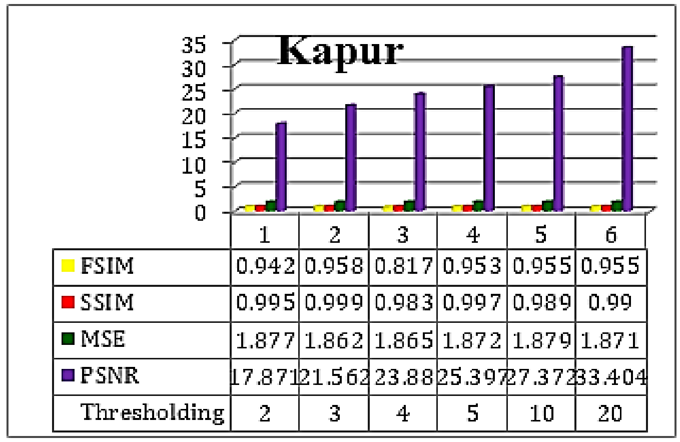

Fig 3: The best statistical measurements of color image in the Kapur method

Figure 3 shows that after applying the JSA algorithm with setting the threshold coefficient of 20, got the best statistical measures which are 33.404, 1.871, 0.990, 0.995 for PSNR, MSE, SSIM and FSIM, respectively.

4.3 Tsallis Entropy Method

The Tsallis method was applied with the Hybrid Jaya algorithm with the Simulated Annealing algorithm (JSA) to choose the best threshold. Experiments were conducted on 8 images, including 5 color images and 3 known grey images. All images are of size (512 ×512) pixels. In this experiment, 10 threshold levels were used to segment the multilevel color image threshold. All experiments were repeated 20 times for each picture and each level. as shown in table(3) below.

Table 3: Use The Tsallis Method.

				JSA			
K	Image	Fmax	Time(S)	PSNR	MSE	SSIM	FSIM
	Im1	23081347216650.4	6.002	33.051	1.866	0.993	0.995
	Im2	38770157652820.2	5.163	32.670	1.845	0.995	0.986
20	Im3	42505466888224.6	6.271	32.476	1.857	0.991	0.967
	Im4	65315886669957.4	3.878	32.748	1.865	0.998	0.984
	Im5	6693130092074.76	4.639	33.408	1.878	0.990	0.989

Im6	**5786779227255.6**	**3.289**	**32.653**	**1.842**	**0.997**	**0.977**
Im7	**5465744929700.8**	**4.007**	**33.371**	**1.798**	**0.990**	**0.955**
Im8	**5052276360088.14**	**2.482**	**32.499**	**1.858**	**0.998**	**0.994**

Relying on the results mentioned in table(3), it was found that the best threshold of 20 achieved the best results when applied in most of the images, depending on the value of the PSNR, where the threshold of 20 achieved the best PSNR in the image Im5, and SSIM, FSIM, MSE and PSNR were also calculated. As shown in Figure 4:

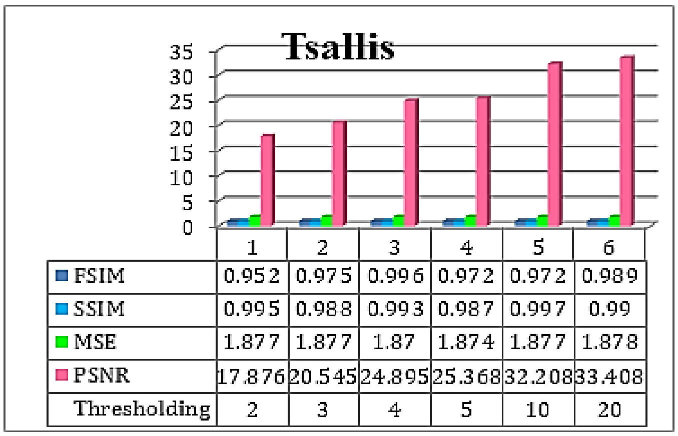

Fig 4: The best statistical measures of a color image in Tsallis method

4.4 Comparison Results with State Of The Art

In this section, the result of this work is compared with the result of previous studies based on PSNR,SSIM,FSIM,MSE.

Table 4: show the proposed JSA comparison with previous studies

NO	Authors	Year	Th	Algorithms	Image	Method	PSNR	MSE	SSIM	FSIM
1	Ashish Kumar Bhandari.	2020	16	ABC DE BDE JSA	Im3	Kapur	26.792 27.889 28.947 29.655	1.362 1.061 1.124 1.872	0.984 0.993 0.997 0.998	0.950 0.965 0.993 0.995
2	Ashish Kumar Bhandari.	2020	16	PSO ABC BDE JSA	Im2	Tsallis	25.038 27.353 27.003 30.294	2.039 1.196 1.012 1.870	0.917 0.993 0.991 0.994	0.682 0.957 0.957 0.966
3	Lifang He, Songwei Huang.	2020	6	EKH MFA WCA BA JSA	Im4	Tsallis	16.474 16.473 16.474 16.474 26.628	-- - - - -	0.927 0.927 0.927 0.927 0.980	- - - - -
4	Lifang He, Songwei Huang.	2020	6	EKH MFA WCA BA JSA	Im4	Kapur	16.479 16.479 16.478 16.478 26.680	- - - - -	0.940 0.940 0.940 0.939 0.999	- - - - -

5. Conclusion

Several applications have used image segmentation as a preprocessing step since it has received more attention. There are other techniques for segmenting images, but multilevel thresholding is the most well-liked and effective one. This approach turns the issue into an optimization problem, which is then solved utilizing a variety of swarm methodologies and fitness functions such Otsu's function, Tsallis entropy, and Kapur functions. These swarm algorithms may not converge to the ideal threshold values that enhance the image segmentation since they are constrained by issues like being stuck at a local point, and the computational complexity increases in the multilevel threshold. To solve this problem, the Jaya algorithm was hybridized with the Simulated Annealing algorithm. The thresholding methods used are illustrated by the Otsu, Kapur and Tsallis method. Then the results of each method used were presented with the JSA algorithm, which was applied to 8 color and gray images.

The Tsallis method achieved the best results (33.408, 1.878, 0.990, 0.989) for the PSNR, MSE, SSIM, FSIM.

As for Otsu method, it achieved results (30.532, 1.868, 0.993, 0.995) for the PSNR, MSE, SSIM, FSIM.

Kapur method achieved results (33.404, 1.871, 0.990, 0.955) for the PSNR, MSE, SSIM, FSIM.

Compared with the results of previous studies, the proposed method showed superiority and obtained better results than previous studies compared with it in the tables 4.

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عتبة صورة متعددة المستويات تعتمد على خوارزمية جايا الهجينة والتليين المحاكي

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الخلاصة:

العتبة هي طريقة لتجزئة الصورة على أساس المنطقة ، وهو أمر مهم في تطبيقات معالجة الصور مثل التعرف على الكائنات متعدد المستويات. يتم استخدام العتبة لإيجاد قيم عتبة متعددة. يلعب تجزئة الصور دورًا مهمًا في تحليل الصور والتعرف على الأنماط. في حين أن تقنيات العتبة تقليدية جيدة تمامًا لخوارزميات العتبة ثنائية المستوى ، فإن العتبة متعددة المستويات للصور الملونة قد تحتوي على الكثير من التعقيد في المعالجة. كثيرًا ما يتم استخدام أساليب ذكاء الحشد لتقليل تعقيد مشكلات التحسين المقيدة المطبقة على العتبات متعددة المستويات وتجزئة الصور الملونة (RGB) ؛ في هذا البحث تم اقتراح خوارزمية جايا الهجينة مع خوارزمية SA لحل مشكلة التعقيد الحسابي في العتبة متعددة المستويات. يستخدم هذا العمل طريقة Otsu و Kapur entropy و Tsallis كتقنيات للعثور على القيم المثلى للعتبات عند مستويات مختلفة من الصور الملونة حيث تم إجراء تجارب المهام المستهدفة على 5 صور ملونة موحدة و 3 صور ذات تدرج رمادي فيما يتعلق بقيم العتبة المثلى ، تم استخدام الأساليب الإحصائية لقياس أداء طرق العتبة واختيار أفضل عتبة ، وهي PSNR و SSIM و FSIM و MSE وقيم الهدف على العديد من المستويات. تشير النتائج التجريبية إلى أن طريقة جايا والتليين المحاكي (JSA) لمقدم العرض أفضل من الطرق الأخرى لتقسيم الصور الملونة (RGB) بمستويات عتبة متعددة. من ناحية أخرى ، تم العثور على إنتروبيا Tsallis في السلسلة لتكون أكثر قوة ودقة في تقسيم الصور الملونة على مستويات متعددة.