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Adaptive Cuckoo Search based Image Segmentation

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Abstract: Image segmentation is a method of segregating the image into required segments/regions. Image thresholding being a simple and effective technique, mostly used for image segmentation and these thresholds are optimized by optimization techniques by maximizing the Shannon and Fuzzyentropy. However, as the two level thresholding is extends to multi-level thresholding, the computational complexity of the algorithm is further increased. So there is need of evolutionary and swarm optimization techniques. In this paper, first time optimal thresholds are obtained by maximizing the Shannon and Fuzzyentropy by using novel adaptive cuckoo search algorithm (ACS). The proposed ACS algorithm performance of image segmentation is tested using natural and standard images. Experiments shows that proposed ACS is better than firefly algorithm (FA) and cuckoo search (CS).
Keywords: image segmentation, image thresholding, Shannon and Fuzzy entropy, cuckoo search, firefly algorithm

I. INTRODUCTION

Image segmentation is the pre-process step of image compression, pattern recognition, medical imaging applications, bio-medical imaging, remote sensing etc. There are many applications of image segmentation in the literature including synthetic aperture radar (SAR) image extraction, brain tumor extraction etc. The main impartial of image segmentation is to excerpt numerous features of the image which can be fused or divided in order to figure objects of attention on which examination and interpretation can be accomplished. Image segmentation represents first step in image compression and pattern recognition. There are so many ways to image segmentation. The simplest and easy ways of image segmentation is image thresholding. Thresholding approaches are of two types one is nonparametric and parametric. In nonparametric approach thresholding is performed based on class variance as in otsu's method or established on an entropy criterion, such as Tsallis entropy, Fuzzy entropy and Kapur's entropy [1]. If the image is partitioned into two classes, i.e. object and background, then the threshold is termed bi-level threshold else multi-level threshold. Thresholding technique has so many real time applications like data, image and video compression, image recognition, pattern recognition, image understanding and communication. Sezgin[2] performed comparative study on image thresholding, they classified the image thresholding into six categories. Kapur classifies the image into some classes by calculating threshold which is based on the histogram of the gray level image [3]. Otsu's method classifies the image into some classes by calculating threshold which is based on between-class variance of the pixel intensities of that class [4]. These two methods are under the category of bi-level thresholding and found efficient in case of two thresholds, but for multi-level thresholding the computational complexity is very high. Entropy may be a Shnnon, fuzzy, between class variations, Kapur's entropy, minimization of the Bayesian error and Birge–Mass art thresholding strategy. The disadvantage of these techniques is that convergence time or computational time or CPU time is exponential increasing with the problem. So alternative to these techniques which minimizes the CPU time for the same problem is evolutionary and swarm-based calculation techniques. Sathya and Kayalvizhi[5] applied bacterial foraging optimization algorithm (BF) for optimizing objective functions, so achieved efficient image segmentation. Further to improve convergence speed and the global searching ability of BF, they modified swarming step and reproduction step, so improved the robustness of BF and achieved fast convergence. Mbuyamba[6] used Cuckoo Search (CS) algorithm for energy minimization of alternative Active Contour Model (ACM) for global minimum and exhibited that polar coordinates with CS is better than rectangular. There are so many optimization techniques are available in the literature, in which a few are used for bi-level thresholding for ordinary image segmentation, Ye [7] used fuzzy entropy with bat algorithm (BA) and compared the results with artificial bee colony algorithm (ABC), ant colony (ACO), PSO and Genetic algorithm (GA). Agrawal[8] used Tsallis entropy with CS algorithm and compared the results with BF, PSO and GA. Horng used firefly algorithm (FA) for multilevel image thresholding [9]. Kapur's and Otsu's entropy methods are simple and effective but computationally affluent when prolonged to multilevel thresholding since they hirea comprehensive search for optimal thresholds. Bhandari[10] proposed Tsallis entropy based multilevel thresholding for colored satellite image segmentation using high dimensional problem optimizer that is Differential Evolution (DE), WDO, PSO and Artifical Bee Colony (ABC).

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In this paper, first time we applied ACS based image thresholding for image segmentation by optimizing the Shannon and Fuzzy entropy and compared the results with other optimization techniques such as FA and CS. For the performance evaluation of proposed ACS based image thresholding we consider objective function value, Misclassification errorand Structural Similarity Index (SSIM). In all parameters the proposed algorithm performance is better compared than FA and CS.

II. CONCEPT OF SHANNON AND FUZZY ENTROPY

A. *Concept of Shannon Entropy*

Entropy is the compressive procedure of information which results higher rate of compression and high speed of transmission which compresses the required number of bits depending on the observation of repetitive information/message. If there are $N = 2^n$ (if $N = 8$) messages to transmit, n ($n = 3$) bits are required, then for each of N messages, number of bits required is log_2^N bits. If one observes the repetition of same message from a collection of N messages as well as the messages can be assigned a non-uniform probability distribution, it will be possible to use fewer than logN bits per message. This is introduced by Claude Shannon based on the Boltzmann's H-theorem and is called as Shannon entropy, Let X is random variable (discrete) with elements $\{X_1, X_2 \ldots, X_n\}$, then probability mass function $P(X)$ is given as

$$H(X) = E[I(X)] = E[-\ln(P(X))] \quad (1)$$

Where E is the expected value operator, I show the content of information and $I(X)$is also a random variable. Further the Shannon entropy is re-written as in Eq (2) and is considered as the objective function which is to be optimized with optimization techniques.

$$H(X) = \sum_{i=1}^{n} P(x_i) I(x_i) = -\sum_{i=1}^{n} P(x_i) log_b P(x_i) \quad (2)$$

Where b base of the algorithm in general it is equal to 2. If $P(x_i) = 0$ for some i then the multiplier $0log_b0$ is considered as zero, which is consistent with the limit.

$$\lim_{P\to 0+} plog(p) = 0 \quad (3)$$

The said equations are for discrete value of X and the same are applicable for continuous values of X by replacing summation with integer.

B. *Concept of Fuzzy Entropy*

Let $D=\{(i,j):i=0,1,2,\ldots,M-1; j=0,1,2,\ldots N-1\}$ and $G=\{0,1,2,\ldots,L-1\}$, Where M is width of image, N is height of image and L is number of gray level in image. $I(x,y)$ is the intensity of image at position (x,y) and $D_k = \{(x,y):I(x,y) = k, (x,y) = D\}, k=0,1,2,\ldots,L-1$. Let us assume two thresholds i.e. T_1, T_2 which divide the domain D of the original image into three regions such as E_d, $E_m$and E_b. E_d region covers the pixels whose intensity value is less than T_1, E_m contains the pixels whose intensity is in between T_1, T_2 and E_b covers the pixels whose intensity is greater than T_2. $\Pi_3=\{E_d, E_m, E_b\}$ is an unknown probabilistic partition of D whose probability distribution is given in (11).$P_d =P(E_d)P_m =P(E_m)P_b =P(E_b)$. μ_d, μ_m and μ_b are the membership functions (μ) of E_d, E_m and E_b respectively and require six parameters like a_1, b_1, c_1, a_2, b_2, c_2. The thresholds T_1 and T_2 values are variable based on the membership functions. For each k=1, 2,…., 255, let

$$D_d=\{(x, y) : I(x, y) \leq T_1, (x, y) \in D_k\} \quad (4)$$

$$Dm= \{(x, y) : T_1< I(x, y) \leq T2, (x, y) \in Dk\} \quad (5)$$

$$Db= \{(x, y) : I(x, y) > t2, (x, y) \in Dk\} \quad (6)$$

If the conditional probability of E_d, E_m and $E_b$is $p_{d|k}$, $p_{m|k}$ and $p_{b|k}$ respectively under the circumstance that the pixel pertains to D_k with $p_{d|k} + p_{m|k}+p_{b|k} = 1$(k=0, 1, 2,….., 255) then above equations can be rewritten as

$$p_{kd} = p(D_p) = p_k \times p_{d/k} \quad (7)$$

$$p_{km} = p(D_m) = p_k \times p_{m/k} \quad (8)$$

$$p_{kb} = p(D_b) = p_k \times p_{b/k} \quad (9)$$

Let the grade of pixels with gray level value of k belong to the class dark (E_d), dust (E_m) and bright (E_b) be equivalent to their conditional probability $p_{d|k}$, $p_{m|k}$ and $p_{b|k}$ respectively. Then the following equations will hold as:

$$p_d = \sum_{k=0}^{255} p_k * p_{d/k} = \sum_{k=0}^{255} p_k * \mu_d(k) \tag{10}$$
$$p_m = \sum_{k=0}^{255} p_k * p_{m/k} = \sum_{k=0}^{255} p_k * \mu_m(k) \tag{11}$$
$$p_b = \sum_{k=0}^{255} p_k * p_{b/k} = \sum_{k=0}^{255} p_k * \mu_b(k) \tag{12}$$

The fuzzy membership functions are drawn and shown in Fig. 1. The function Z ($k, a_1, b_1, c_1, a_2, b_2, c_2$), U($k, a_1, b_1, c_1, a_2, b_2, c_2$) and S($k, a_1, b_1, c_1, a_2, b_2, c_2$) are assigned as membership functions of class dark $\mu_d(k)$, dust $\mu_m(k)$ and bright $\mu_b(k)$ respectively. Then the membership functions are given as

$$\mu_d(k) = \begin{cases} 1 & k \le a_1 \\ 1 - \dfrac{(k-a_1)^2}{(c_1-a_1)*(b_1-a_1)} & a_1 < k \le b_1 \\ \dfrac{(k-c_1)^2}{(c_1-a_1)*(c_1-b_1)} & b_1 < k \le c_1 \\ 0 & k > c_1 \end{cases} \tag{13}$$

$$\mu_m(k) = \begin{cases} 0 & k \le a_1 \\ \dfrac{(k-a_1)^2}{(c_1-a_1)*(b_1-a_1)} & a_1 < k \le b_1 \\ 1 - \dfrac{(k-c_1)^2}{(c_1-a_1)*(c_1-b_1)} & b_1 < k \le c_1 \\ 1 & c_1 < k \le a_2 \\ 1 - \dfrac{(k-a_2)^2}{(c_2-a_2)*(b_2-a_2)} & a_2 < k \le b_2 \\ \dfrac{(k-c_2)^2}{(c_2-a_2)*(c_2-b_2)} & b_2 < k \le c_2 \\ 0 & k > c_2 \end{cases} \tag{14}$$

$$\mu_b(k) = \begin{cases} 0 & k \le a_2 \\ \dfrac{(k-a_2)^2}{(c_2-a_2)*(b_2-a_2)} & a_2 < k \le b_2 \\ 1 - \dfrac{(k-c_2)^2}{(c_2-a_2)*(c_2-b_2)} & b_2 < k \le c_2 \\ 1 & k > c_2 \end{cases} \tag{15}$$

The above said equations are written by assuming $0 \le a_1 < b_1 < c_1 < a_2 < b_2 < c_2 \le 255$. Then, the fuzzy entropy function of each class could be given as (12)

$$H_d = -\sum_{k=0}^{255} \frac{p_k * \mu_d(k)}{p_d} * \ln\left(\frac{p_k * \mu_d(k)}{p_d}\right) \tag{16}$$
$$H_m = -\sum_{k=0}^{255} \frac{p_k * \mu_m(k)}{p_m} * \ln\left(\frac{p_k * \mu_m(k)}{p_m}\right) \tag{17}$$
$$H_b = -\sum_{k=0}^{255} \frac{p_k * \mu_b(k)}{p_b} * \ln\left(\frac{p_k * \mu_b(k)}{p_b}\right) \tag{18}$$

The whole fuzzy entropy is calculated through summarizing fuzzy entropy of each class i.e.

$$H(a_1, b_1, c_1, a_2, b_2, c_2) = H_d + H_m + H_b \tag{19}$$

The above equation is an objective function which is to be optimized with the optimization techniques. Optimization techniques optimize or maximize H (a_1, b_1, c_1, a_2, b_2, c_2) function by varying a_1, b_1, c_1, a_2, b_2, c_2. Once these values are optimized, then threshold values are calculated with the following equation

$$\mu_d(T_1) = \mu_m(T_1) = 0.5 \text{ and } \mu_m(T_2) = \mu_b(T_2) = 0.5 \qquad (20)$$

From Fig. 1 it is observed that T_1 and T_2 are the point of interaction of $\mu_d(k)$, $\mu_m(k)$ and $\mu_b(k)$ curve. From Eqs (13)-(15), the values of T_1 and T_2 calculated with the below equation

$$T_1 = \begin{cases} a_1 + \sqrt{(c_1 - a_1) * (b_1 - a_1) / 2} & (a_1 + c_1)/2 \le b_1 \le c_1) \\ c_1 - \sqrt{(c_1 - a_1) * (c_1 - b_1) / 2} & a_1 \le b_1 \le (a_1 + c_2)/2 \end{cases} \qquad (21)$$

$$T_2 = \begin{cases} a_2 + \sqrt{(c_2 - a_2) * (b_2 - a_2) / 2} & (a_2 + c_2)/2 \le b_2 \le c_2 \\ c_2 - \sqrt{(c_2 - a_2) * (c_2 - b_2) / 2} & a_2 \le b_2 \le (a_2 + c_2)/2 \end{cases} \qquad (22)$$

As per the requirements of researchers, the two level thresholding can be extended to three or more and can be restricted to single level also. For two thresholds the number of parameters to be optimized is six and as levels of increasing number parameters to be optimized is also increasing, so fuzzy entropy takes much time for convergence. Hence two level image thresholding for image segmentation with the Shannon entropy and Fuzzy entropy proved to be efficient and effective but for multilevel thresholding, both entropy techniques consume much convergence time and increase exponential with level of thresholds. The drawback of Shannon entropy and Fuzzy entropy is convergence time. To improve the performance of these methods further and to reduce the convergence time, researchers used applications of optimization techniques such as differential evolution, Particle swarm optimization, Bat algorithm and Firefly algorithm for image thresholding and henceforth image segmentation. These techniques are set to maximize the Shannon entropy and Fuzzy entropy as given in Eq (2) and (19).

C. Novel Adaptive Cuckoo Search Algorithm

The CS algorithm is projected by Yang in 2010 [14] and cuckoos step of walk follows the Levy distribution function and obeys the either Mantegna algorithm or McCulloch's algorithm. In the proposed technique, we follow a specific strategy instead of Levy distribution function. The normal CS does not have any appliance to switch the step size in the repetition process, which can lead the method to extent universal minima or maxima. Here, we try to include a step size which is relative to the suitability of the discrete nest in the search space in the present generation. The tuning parameter α is fixed in the literature. In our proposed algorithm step size follows the following equation [25]

$$step_i(t+1) = \left(\frac{1}{t}\right)^{\left|((bestf(t) - f_i|(t)) \div (bestf(t) - \text{worst } f(t))\right)} \qquad (23)$$

Where t is the iteration search algorithm; $f_i(t)$ is the objective value i^{th} nest in the iteration t; *bestf*(t) is the best objective in iteration t; *worstf*(t) is the worst objective value in the iteration t. Initially high value of step size is considered and is decreasing with the increment in iteration. It shows the algorithm tries to global best solution. From Eq. (24), Step size is depends upon the iterations and it shows adaptive of step size of the algorithm. From the observation step size is adaptive and chooses its value based on the fitness value. The population follows the following equation.

$$X_i(t+1) = X_i(t) + randn \times step_i(t+1) \qquad (24)$$

The major benefit of the naval adaptive cuckoo search is that it does not need any preliminary parameter to be distinct. It is quicker than the cuckoo search algorithm.

$$X_i(t+1) = X_i(t) + randn \times step_i(t+1) \times X_i(t) - X_{gbest} \qquad (25)$$

Where X_{gbest} is the universal solution amongst all X_i for I (for $i = 1, 2, \ldots, N$)at time t.

III. RESULTS AND DISCUSSIONS

For the performance evolution which includes robustness, efficiency and convergence of proposed firefly algorithm, we selected "Lena (1)", "Goldhill (2)", "Pirate (3)" and "starfish (4)" as a test images. All These images are .jpg format images and of size

225×225 and corresponding histograms are shown in Fig. 1. In general, perfect threshold can be selected if the histogram of image peaks is lanky, thin, symmetric, and divided by unfathomable valleys. Goldhill and pirate image histograms peaks are tall, narrow and symmetric, but for Lena image histogram peaks are not tall and narrow so difficult to segment with ordinary methods. So we proposed adaptive cuckoo search algorithm based image thresholding for effective and efficient image segmentation of above said critical images by optimizing Shannon and Fuzzy entropy. The performance and effectiveness of proposed adaptive CS proved better compared to other optimization techniques like FA and CS.

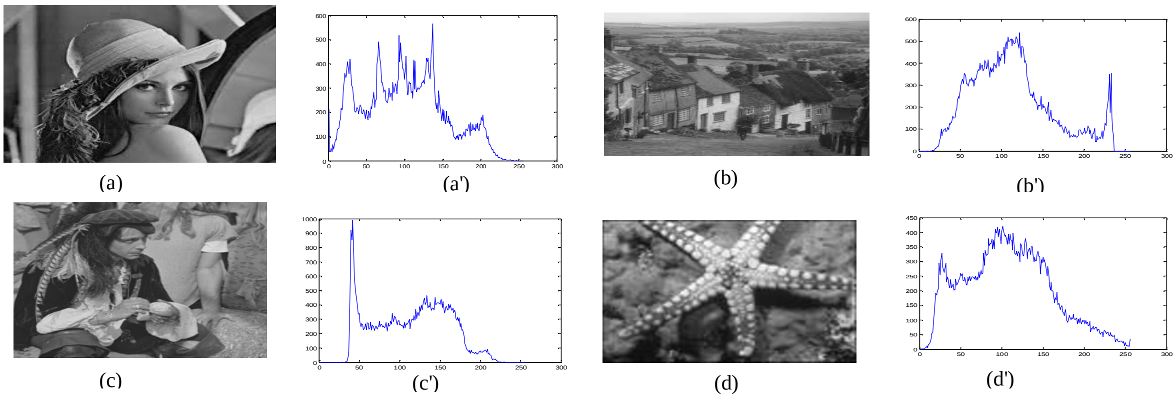

Fig.1. Standard image and respective histograms of three methods a) Lena b)Goldhill c) Pirate d) Satrfish

A. *Maximization of Shannon and Fuzzy entropy*

The ACS and other two algorithms are applied on Shannon and Fuzzy entropy objective function and compared the results of FA and CS. All the algorithms are optimized to maximize the objective function. Table.1show the objective values of ACS, CS and FA. It is observed from Table. 1 that objective values obtained with ACS by using Shannon and Fuzzy entropy is higher than the FA and CS for different images.

Table 1: Comparison of objective values obtained by various algorithms

		Th = 2		Th = 3		Th = 4		Th = 5	
Img	Opt	Shannon	Fuzzy	Shannon	Fuzzy	Shannon	Fuzzy	Shannon	Fuzzy
1	FA	12.77139	14.32151	15.85993	17.95987	18.70631	21.38698	21.38616	24.561514
	CS	12.77218	14.32689	15.86123	17.96543	18.76301	21.38999	21.39009	24.64573
	ACS	12.77339	14.32812	15.87993	17.97987	18.77888	21.40835	21.40912	24.81112
2	FA	12.10478	13.56331	15.15158	17.09854	17.89274	20.27302	20.35085	23.360407
	CS	12.11233	13.58789	15.15158	17.10549	17.94234	20.28123	20.36009	23.379933
	ACS	12.11428	13.59083	15.18515	17.11903	17.97892	20.28909	20.37689	23.388888
3	FA	12.85614	14.03124	16.12298	17.69289	19.06769	21.33981	21.75928	24.754253
	CS	12.87777	14.12345	16.14992	17.70707	19.08393	21.45678	21.78592	24.767772
	ACS	12.88123	14.13244	16.15698	17.71234	19.19494	21.59031	21.79258	24.771256
4	FA	13.01569	14.6113	16.23572	18.33766	19.30959	21.79938	22.12073	25.037815
	CS	13.01753	14.60729	16.28334	18.38907	19.39215	21.87998	22.19901	24.984961
	ACS	13.01853	14.70634	16.29663	18.39909	19.40501	21.88969	22.26587	24.997564

B. *Misclassification error /Uniformity measure*

It is measure of uniformity in threshold image and is used to compare optimization techniques performance. Misclassification error is measured by Eq. 26

$$M = 1 - 2 * Th * \frac{\sum_{j=0}^{Th} \sum_{i \in R_j} (I_i - \sigma_j)^2}{N * (I_{max} - I_{min})^2} \qquad (26)$$

Where *Th* is the number of thresholds which are used to segment the image, R_j is the j^{th} segmented region, I_i is the intensity level of pixel in that particular segmented area, σ_j is the mean of j^{th} segmented region of image, *N* is total number of pixels in the image, I_{min} and I_{max} are the maximum and minimum intensity of image respectively. In general misclassification errors lies between 0 and 1 and higher value of misclassification error shows better performance of the algorithm. Hence, the Uniformity measure in thresholding is measured from the difference between the maximum value, 1 (better quality of image) and minimum value, 0 (worst quality of image). Table.2 shows misclassification error of proposed and other techniques and proved proposed method have lesser misclassification error and shows better visual quality.

C. Structural Similarity Index (SSIM)

It estimates the visual likeness between the input image and the decompressed image/thresholded image and is calculated with below equation

$$SSIM = \frac{(2\mu_I\mu_{\tilde{I}} + C1)(2\sigma_{I\tilde{I}} + C2)}{(\mu_I^{\,2} + \mu_{\tilde{I}}^{\,2} - C1)(\sigma_I^{\,2} + \sigma_{\tilde{I}}^{\,2} - C2)} \qquad (27)$$

Where μI and $\mu\tilde{I}$ are the mean value of the input image I and decompressed image $\tilde{I}$, σ_I and $\sigma_{\tilde{I}}$ are the standard deviation of original image I and reconstructed image $\tilde{I}$, $\sigma_{I\tilde{I}}$ is the cross-correlation and C1 & C2 are constants which are equal to 0.065. Table.3 shows the SSIM of various methods with Shannon and Fuzzy entropy and it demonstrate proposed method SSIM is higher than other methods. Fig. 2 shows the segmented images and respective optimized 5 level thresholds with ACS and it shows segmentation with ACS is better than FA and CS.

Table 2: Comparison of Misclassification error values obtained by various algorithms

		Th = 2		Th = 3		Th = 4		Th = 5	
Img	Opt	Shannon	Fuzzy	Shannon	Fuzzy	Shannon	Fuzzy	Shannon	Fuzzy
1	FA	0.959567	0.94826	0.93835	0.946852	0.867879	0.902922	0.498263	0.7233069
	CS	0.95271	0.93731	0.91860	0.93890	0.85217	0.90187	0.48313	0.718661
	ACS	0.95178	0.92831	0.90150	0.92070	0.88761	0.89235	0.48188	0.710272
2	FA	0.97102	0.93072	0.923627	0.909869	0.796942	0.723765	0.68383	0.6179214
	CS	0.97001	0.92345	0.913627	0.923451	0.795432	0.721823	0.65383	0.6079214
	ACS	0.96897	0.92090	0.910917	0.920988	0.791234	0.713765	0.62383	0.605123
3	FA	0.956984	0.93086	0.943455	0.933864	0.863431	0.896563	0.811681	0.8350455
	CS	0.95520	0.92980	0.94200	0.931770	0.860297	0.89569	0.806531	0.821425
	ACS	0.95513	0.92884	0.94160	0.930070	0.859665	0.893245	0.80554	0.812485
4	FA	0.964161	0.94357	0.925283	0.915473	0.91566	0.902217	0.800406	0.7304659
	CS	0.964089	0.94427	0.920442	0.914187	0.915002	0.90105	0.798476	0.7290859
	ACS	0.963951	0.94051	0.914453	0.913383	0.914091	0.90019	0.786292	0.7289454

Table 3

Comparison of SSIM obtained by various algorithms

		Th = 2		Th = 3		Th = 4		Th = 5	
Img	Opt	Shannon	Fuzzy	Shannon	Fuzzy	Shannon	Fuzzy	Shannon	Fuzzy
1	FA	0.706563	0.69509	0.775408	0.700278	0.797999	0.732765	0.83524	0.7979711
	CS	0.70895	0.69909	0.77923	0.711089	0.798996	0.734453	0.836085	0.7980472
	ACS	0.70931	0.70662	0.779972	0.747751	0.800821	0.710816	0.839444	0.799019
2	FA	0.655872	0.645513	0.741531	0.694545	0.786991	0.732217	0.822033	0.8096297
	CS	0.661256	0.66495	0.77309	0.717896	0.80078	0.74784	0.838786	0.810092
	ACS	0.679484	0.67148	0.78689	0.729373	0.81937	0.750465	0.84775	0.820192
3	FA	0.670661	0.61131	0.754686	0.720464	0.801608	0.819659	0.745729	0.8431184
	CS	0.682929	0.63939	0.754729	0.722939	0.805001	0.820921	0.751023	0.844123
	ACS	0.69020	0.63838	0.754928	0.725828	0.806221	0.821391	0.769901	0.853421

4	FA	0.584474	0.52503	0.682892	0.765436	0.721905	0.719282	0.78991	0.7724659
	CS	0.584742	0.58382	0.687281	0.779821	0.733932	0.722828	0.791383	0.7984992
	ACS	0.584812	0.58931	0.689112	0.789392	0.749912	0.723372	0.792992	0.8349492

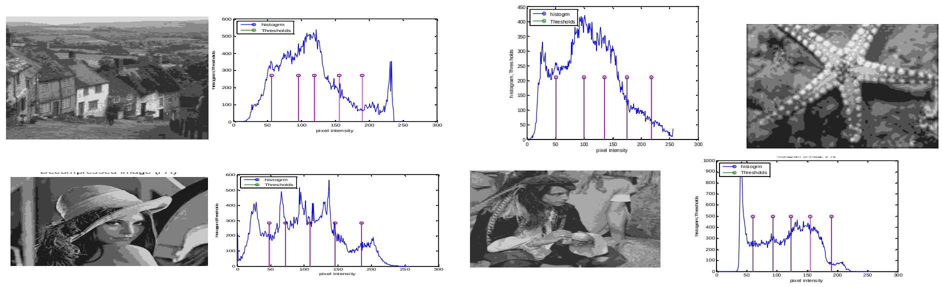

Fig.2. Segmented images and respective optimized 5 level thresholds with ACS

IV. CONCLUSIONS

In this paper, we proposed natural inspired adaptive cuckoo search algorithm based multilevel image thresholding for image segmentation. ACS maximizes the Fuzzy and Shannon entropy for efficient and effective image thresholding. The proposed algorithm is tested on natural images to show the merits of the algorithm. The results of the proposed method are compared with other optimization techniques such as FAand CS with Shannon and Fuzzy entropy. From the experiments we observed that proposed algorithm has higher/maximum fitness value compared to FA and CS. The SSIM value shows higher values with proposed algorithm than FA and CS. It is concluded that proposed algorithm outperform the FA and CS in all performance measuring parameters.

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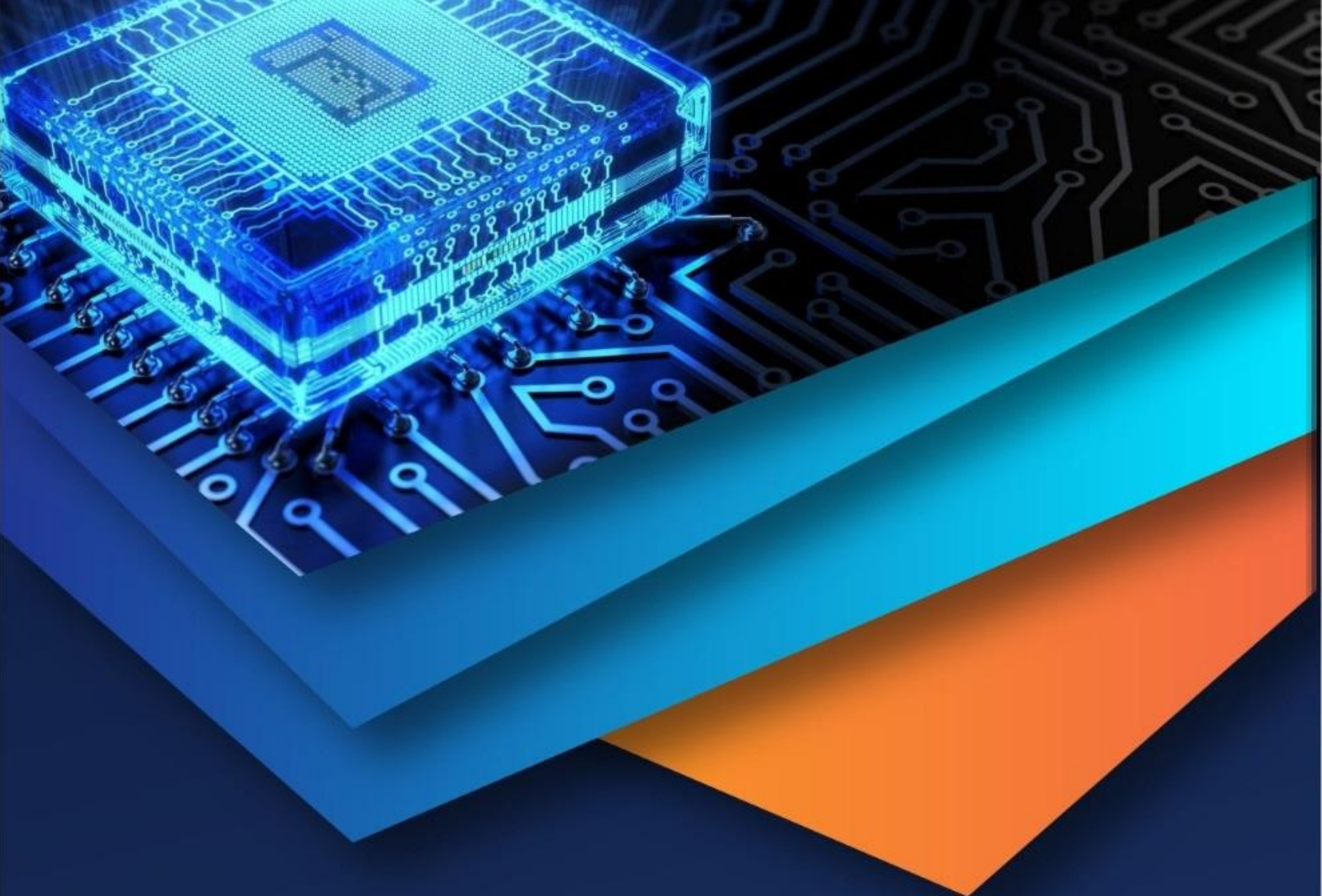

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