Multilevel Image Thresholding for Image Segmentation by ACS algorithm

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Abstract

Image thresholding is the process of extracting objects in a scene from the background accompanies for the analysis and interpretation of image which is mostly employed for its advanced simplicity, robustness, less convergence time and accuracy. The main intend of image segmentation is to segregate the foreground from background. As ordinary thresholding method of image segmentation is computationally expensive while extending for multilevel image thresholding, the need for optimization techniques is highly recommended. The so called optimization techniques such as Particle swarm optimization and bat algorithm undergo instability when the particle velocity is maximum and stagnation stage attributable to quick exploration. This paper proposes for the multilevel image thresholding for image segmentation by using Shannon/fuzzy entropy maximized by naturally inspired Adaptive cuckoo search algorithm.The results are proved better in misclassification,PSNR, Structural Similarity Index and segmented image quality while comparing with differential evolution, Particle swarm optimization and bat algorithm.

1. 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. 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'smethod 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–Massartthresholding 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 thresholdingsince they hireacomprehensive 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).

In this paper, 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 DE,PSO and BA For the performance evaluation of proposed ACS based image thresholding we consider objective function value, Misclassification error,PSNR and Structural Similarity Index (SSIM). In all parameters the proposed algorithm performance is better compared than DE,PSO and BA.

2. Concept of Shannon and Fuzzy Entropy

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

$$H(X) = E[I(X)] = E[-\ln(P(X))] \tag{1}$$

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.

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

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.

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

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

Concept of Fuzzy Entropy: Let $D=\{(i,j):i=0,1,2,\ldots..,M-1;\ j=0,1,2,\ldots\ldots N-1\}$ and $G=\{0,1,2,\ldots\ldots,L-1\}$, 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. Π_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

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

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

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

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:

$$p_d = \sum_{k=0}^{255} p_k * p_{d/k} = \sum_{k=0}^{255} p_k * \mu_d(k) \quad (10)$$

$$p_m = \sum_{k=0}^{255} p_k * p_{m/k} = \sum_{k=0}^{255} p_k * \mu_m(k) \quad (11)$$

$$p_b = \sum_{k=0}^{255} p_k * p_{b/k} = \sum_{k=0}^{255} p_k * \mu_b(k) \quad (12)$$

Then, the fuzzy entropy function of each class could be given as (12)

$$H_d = -\sum_{k=0}^{255} \frac{p_k * \mu_d(k)}{p_d} * \ln\left(\frac{p_k * \mu_d(k)}{p_d}\right) \quad (13)$$

$$H_m = -\sum_{k=0}^{255} \frac{p_k * \mu_m(k)}{p_m} * \ln\left(\frac{p_k * \mu_m(k)}{p_m}\right) \quad (14)$$

$$H_b = -\sum_{k=0}^{255} \frac{p_k * \mu_b(k)}{p_b} * \ln\left(\frac{p_k * \mu_b(k)}{p_b}\right) \quad (15)$$

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

$$H(a_1, b_1, c_1, a_2, b_2, c_2) = H_d + H_m + H_b \quad (16)$$

The above equation is an objective function which is to be optimized with the optimization techniques.

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]

$$step_i(\mathrm{t}+1) = \left(\frac{1}{t}\right)^{\left|((bestf\,(\mathrm{t}) - f_i\left|(\mathrm{t})\right) \div (bestf\,(\mathrm{t}) - \mathrm{worst}\, f\,(\mathrm{t}))\right)} \qquad (17)$$

Where t is the iteration search algorithm; $f_i(t)$ is the objective value ith 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.

$$X_i\,(t + 1) = X_i\,(t) + randn \times step_i\,(t + 1) \qquad (18)$$

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.

$$X_i\,(t + 1) = X_i\,(t) + randn \times step_i\,(t + 1) \times\ X_i\,(t) - X_{gbest} \qquad (19)$$

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

3. 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. The performance and effectiveness of proposed adaptive CS proved better compared to other optimization techniques like DE,PSO and BA

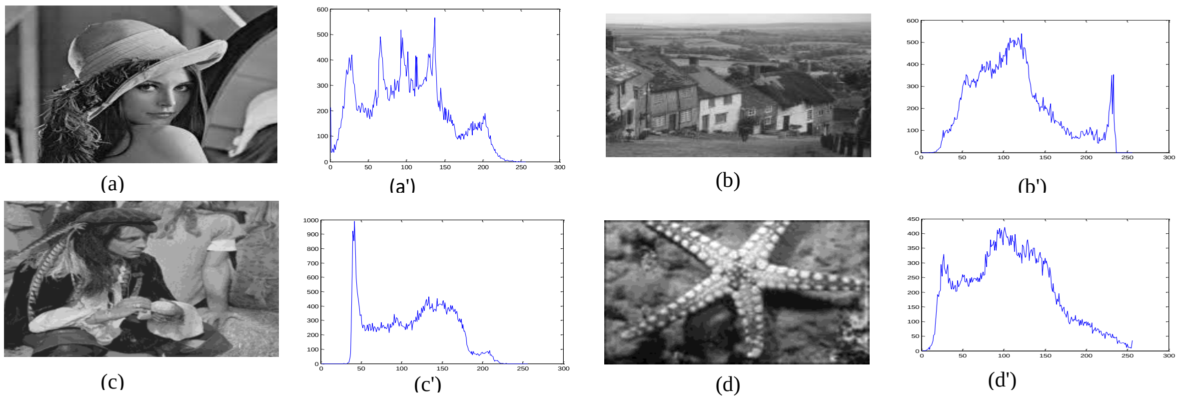

Fig.1. Standard image and respective histograms of three methods a) Lena b)Goldhill c) Pirate d) Satrfish

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

Table.1: Comparison of objective values obtained by various algorithms

		Th = 2		Th = 3		Th = 4		Th = 5	
Image	**Opt Tech**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**
Lena	DE	12.7748	14.123	15.8983	17.5858	18.7812	20.6693	21.4863	24.0294
	PSO	12.7748	14.227	15.8983	17.9142	18.7799	21.1475	21.48382	24.3009
	BA	12.772	14.238	15.8625	17.9398	18.6998	21.2985	21.37358	24.3738
	CS	12.9722	14.4272	15.9612	17.9654	18.9632	21.4912	21.89009	24.6457
	ACS	13.7734	15.3281	16.8799	18.6799	19.2789	22.2084	22.40912	25.8111
Goldhill	DE	12.0745	13.44	15.1319	16.8236	17.8632	19.8954	20.09336	22.9348
	PSO	12.1048	13.533	15.1534	17.0209	17.9031	20.0989	20.43108	22.9835
	BA	12.1048	13.539	15.1534	17.0875	17.8964	20.1657	20.42713	23.2359
	CS	12.1123	13.588	15.1515	17.1055	17.9423	20.2812	20.36009	23.3799
	ACS	13.9143	14.591	15.9852	18.2194	17.9789	21.3891	21.37689	24.3889
Pirate	DE	12.8497	13.88	16.098	17.7611	18.9921	21.0395	21.66071	24.3738
	PSO	12.8561	14.006	16.1206	17.9147	19.0442	21.2423	21.73602	24.561
	BA	12.8561	14.013	16.123	17.974	19.0677	21.3629	21.75813	24.7666
	CS	12.8778	14.123	16.4499	17.7071	19.0839	21.4568	21.78592	24.7678
	ACS	13.6812	15.1321	17.157	18.7123	20.1949	22.5903	22.79258	25.7713
Starfish	DE	13.0153	14.463	16.2266	18.4334	19.285	21.3477	22.06587	24.3756
	PSO	13.0153	14.507	16.2334	18.2591	19.2922	21.68	22.09901	24.8496
	BA	13.0157	14.513	16.2357	18.2981	19.3095	21.7434	22.11218	25.1048
	CS	13.0175	14.607	16.2833	18.3891	19.3922	21.889	22.19901	25.1849
	ACS	14.0185	15.706	16.9966	19.3991	20.405	22.8797	23.26587	26.2975

3.1. 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

$$M = 1 - 2 * Th * \frac{\sum_{j=0}^{Th} \sum_{i \in R_j} (\mathrm{I}_i - \sigma_j)^2}{N * (\mathrm{I}_{\max} - \mathrm{I}_{\min})^2} \quad (20)$$

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.

Table.2 shows misclassification error of proposed and other techniques and proved proposed method have lesser misclassification error and shows better visual quality.

Table 2: Comparative misclassification error (in%) for the thresholding methods under evaluation

		Th = 2		Th = 3		Th = 4		Th = 5	
Im	**Opt Tech**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**
Lena	DE	0.97252	0.968633	0.94903	0.95537	0.90205	0.93939	0.797211	0.8933
	PSO	0.97211	0.959245	0.94533	0.952794	0.90033	0.93573	0.788436	0.80738
	BA	0.97206	0.951017	0.94327	0.949908	0.89664	0.91756	0.759788	0.7288
	CS	0.95276	0.937304	0.91862	0.93892	0.85213	0.90182	0.75314	0.72862
	ACS	0.95182	0.928365	0.90159	0.92069	0.83764	0.87231	0.72182	0.70522
Goldhill	DE	0.97189	0.971564	0.94268	0.950803	0.82816	0.89522	0.831336	0.68868
	PSO	0.97175	0.947282	0.93871	0.938885	0.82068	0.85344	0.709158	0.6833
	BA	0.9712	0.938959	0.93141	0.92963	0.81576	0.74867	0.701747	0.66378
	CS	0.97023	0.92345	0.91363	0.903451	0.79543	0.72182	0.673838	0.61792
	ACS	0.96897	0.9109	0.90092	0.88988	0.78123	0.71376	0.62383	0.60012
Pirate	DE	0.97055	0.946298	0.95707	0.951736	0.92264	0.91885	0.902752	0.90609
	PSO	0.96696	0.933165	0.95583	0.95061	0.91121	0.90398	0.840729	0.90519
	BA	0.96128	0.931228	0.95419	0.944304	0.88631	0.90014	0.814228	0.87133
	CS	0.9552	0.9298	0.942	0.931770	0.8603	0.89569	0.806531	0.82143
	ACS	0.94513	0.92884	0.9316	0.92007	0.85967	0.87325	0.80554	0.81249
Starfish	DE	0.96929	0.95527	0.95544	0.974187	0.9378	0.92819	0.898476	0.85609
	PSO	0.96965	0.952507	0.95445	0.953383	0.92679	0.92738	0.826292	0.78945
	BA	0.96791	0.94859	0.95307	0.93925	0.92614	0.91061	0.805522	0.77132
	CS	0.96409	0.94427	0.92044	0.914194	0.915	0.90105	0.798476	0.72909
	ACS	0.95395	0.93051	0.91445	0.903383	0.88409	0.86019	0.786292	0.70895

3.2. 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

$$SSIM = {(2\mu_I \mu_{\tilde{I}} + C1)(2\sigma_{I\tilde{I}} + C2)} \Big/ {(\mu_I^2 + \mu_{\tilde{I}}^2 - C1)(\sigma_I^2 + \sigma_{\tilde{I}}^2 - C2)} \qquad (21)$$

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. Table.4 gives PSNR values obtained by various algorithms and it is concluded that proposed ACS method obtained higher PSNR values than other algoriyhms.Fig. 2 shows the segmented images and respective optimized 5 level thresholds with ACS

Table 3: Comparison of structural similarity index (SSIM) for various algorithms.

		Th = 2		Th = 3		Th = 4		Th = 5	
Im	**Opt Tech**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**
Lena	DE	0.64093	0.656616	0.76657	0.747751	0.78122	0.77082	0.818869	0.82105
	PSO	0.70595	0.663094	0.76923	0.711089	0.7854	0.73445	0.83085	0.76705
	BA	0.70635	0.663156	0.77175	0.745134	0.79574	0.74506	0.831631	0.78958
	CS	0.71895	0.69909	0.77923	0.751089	0.7992	0.76445	0.836085	0.81805
	ACS	0.79931	0.78662	0.82992	0.817751	0.83682	0.82082	0.85944	0.84902
Goldhill	DE	0.64321	0.441218	0.71694	0.644457	0.72	0.67015	0.768224	0.7811
	PSO	0.64449	0.474546	0.7208	0.667122	0.76952	0.68994	0.789104	0.79092
	BA	0.64502	0.606807	0.72873	0.668688	0.78326	0.72731	0.794268	0.79151
	CS	0.68126	0.66495	0.75309	0.717896	0.80078	0.74784	0.838786	0.81009
	ACS	0.72948	0.71458	0.78689	0.79373	0.81937	0.78047	0.87775	0.84019
Pirate	DE	0.64762	0.562101	0.74894	0.662256	0.81562	0.76353	0.859702	0.78116
	PSO	0.70054	0.565558	0.75131	0.704156	0.70892	0.78469	0.804356	0.80291
	BA	0.65315	0.566939	0.74623	0.716693	0.80351	0.78548	0.859187	0.8158
	CS	0.69293	0.67939	0.74473	0.732939	0.8205	0.82092	0.87602	0.84412
	ACS	0.7402	0.72838	0.81493	0.795828	0.87612	0.86139	0.89901	0.877342
Starfish	DE	0.55566	0.493903	0.67386	0.541492	0.68959	0.65329	0.733556	0.70674
	PSO	0.58346	0.494132	0.67654	0.565434	0.71169	0.69186	0.778901	0.72836
	BA	0.58348	0.517186	0.67912	0.620772	0.71976	0.69612	0.783393	0.76676
	CS	0.58474	0.56382	0.68728	0.679821	0.73393	0.72283	0.791383	0.7785
	ACS	0.63481	0.61931	0.72911	0.719392	0.77991	0.75337	0.84299	0.83495

Table 4: Comparison of PSNR values for the methods under evaluation.

		Th = 2		Th = 3		Th = 4		Th = 5	
Im	**Opt Tech**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**	**Shannon**	**Fuzzy**
Lena	DE	28.4478	28.6276	29.6949	28.6481	29.9438	29.1021	31.27988	29.8851
	PSO	28.5097	28.7274	29.7683	29.3717	29.9611	29.1572	31.42467	30.1187
	BA	28.6124	28.742	29.8104	29.5076	29.988	29.5213	31.52876	30.2771
	CS	28.3168	28.4456	29.7723	29.7901	30.0264	29.9436	31.6694	30.337
	ACS	29.7611	29.7205	30.969	30.736	30.4317	30.9853	32.4386	32.489
Goldhill	DE	29.1043	28.8427	29.3906	28.9637	30.2665	29.2554	30.57502	30.6413
	PSO	29.1954	29.0318	29.4628	29.1168	30.5352	29.5548	30.68128	30.7302
	BA	29.2248	29.0657	29.4769	29.4898	30.6566	30.0733	30.79411	30.9964
	CS	29.3939	29.2123	29.5101	29.6123	30.8101	30.3939	31.5373	31.5788
	ACS	30.4333	30.3123	30.6123	30.7818	31.5123	31.9567	32.6234	33.6706.
Pirate	DE	28.7726	28.7004	29.663	29.5453	29.9055	30.3487	30.98535	30.5687
	PSO	28.7977	28.7038	29.8047	29.7589	30.3529	30.8305	31.53031	31.0817
	BA	28.9336	28.7385	29.8116	29.8286	30.8872	31.1737	32.25503	31.2118
	CS	29.8276	28.8266	29.699	29.6767	30.9709	31.151	31.6556	32.2008
	ACS	30.818	30.6326	31.7836	31.6233	31.8646	32.2811	33.3083	33.7394
Starfish	DE	28.4711	28.7096	29.3495	28.6613	29.5639	29.306	29.83035	29.7045
	PSO	28.5689	28.32849	29.3904	28.9917	29.7348	29.4915	30.40952	30.1118
	BA	28.6112	28.7013	29.4363	29.0443	29.7718	29.5343	30.59676	30.2872
	CS	28.655	28.58	29.3623	29.155	29.7426	29.976	30.395	30.418
	ACS	29.534	29.4483	30.7939	30.5854	30.994	30.875	31.3089	31.462

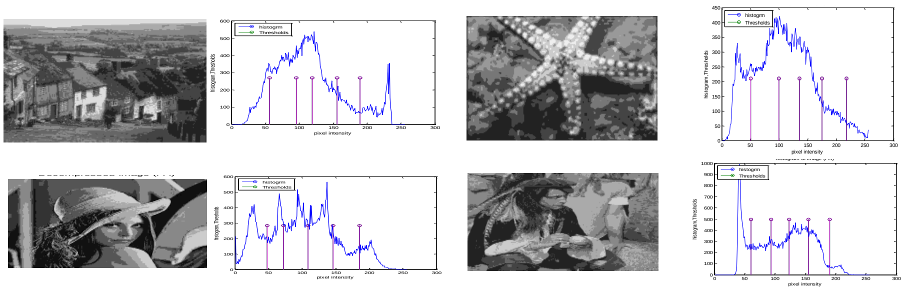

Fig.2. Segmented images and respective optimized 5 level thresholds with ACS

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 DE,PSO and BA. From the experiments we observed that proposed algorithm has higher/maximum fitness value compared to DE,PSO and BA. The SSIM value shows higher values with proposed algorithm than DE,PSO and BA. It is concluded that proposed algorithm outperform the DE,PSO and BA in all performance measuring parameters.

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