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Multilevel Image Thresholding for Image Segmentation using Hybrid Algorithm

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Abstract*: *Image thresholding is an extraction method of objects from a background scene, which is used most of the time to evaluate and interpret images because of their advanced simplicity, robustness, time reduced, and precision. The main objective is to distinguish the subject from the background of the image segmentation. As the ordinary image segmentation threshold approach is computerized costly while the necessity for optimization techniques are highly recommended for multi-tier image thresholds. Level object segmentation threshold by using Shannon entropy and Fuzzy entropy maximized with hGSA-PS. An entropy maximization of hGSA-PS dependent multilevel image thresholds is developed, where the results are best demonstrated in PSNR, misclassification, structural similarity index and segmented image quality compared to the Firefly algorithm, adaptive cuckoo search algorithm and the search algorithm gravitational.

***Keywords* : Entropy, Image thresholding, PNR, SSIM..**

I. INTRODUCTION

Image thresholding is the process of extracting objects in a scene from the background that helps for analysis and interpretation of image. It is a challenging task for the researchers in image processing to select a preeminent gray level threshold that extracts the object from the background of the gray level image or color image. Selection of threshold is moderately simple in the case where histogram of the image has a deep valley representing background and sharp edges representing objects, but due to the multimodality of the histograms of many image selections of a threshold is difficult task. So researchers proposed many techniques for preeminent gray level threshold. Though there are so many segmentation techniques are in the literature, thresholding is mostly used for its advanced simplicity, robustness, less convergencetime and accuracy.

In this paper the researchers have applied hybrid Gravitational search and pattern search algorithm(hGSA-PS) for image thresholding by optimizing the Shannon/Fuzzy entropy and compared the results with previous optimization techniques such as GSA,ACS and FA . For the performance evolution of proposed firefly algorithm based image thresholding, we considered objective function value,structural similarity index, peak signal to noise ratio, misclassification error. In all performance measuring parameters the proposed algorithm performance is better when compared to other FA, ACS and GSA.

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II. PROBLEM FORMULATION OF OPTIMUM THRESHOLDING METHODS

Image thresholding is a process of converting a grayscale input image to a black and white image by using optimal thresholds. Thresholding may be a local or global but these methods are computationally expensive, so there is a need of optimization techniques which optimize the objective function results in the reduction of computational time of local or global methods.

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.

B. Concept of Fuzzy Entropy

Let D={(i,j):i=0,1,2,…..,M-1; j=0,1,2,…….N-1} and G={0,1,2,……,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,…..,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 as (Zhao et. al, 2001) $P_d = P(E_d) P_m = P(E_m) P_b = P(E_b)$. 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.

III. OVERVIEW OF GRAVITATIONAL SEARCH ALGORITHM AND PATTERN SEARCH

A. **Gravitational Search Algorithm (GSA):** GSA is a metharustic optimization algorithm which is based on the newton laws of gravity and motion (Rashediet al., 2011). In GSA, performance of object is measured by its mass.

B. The gravitational force causes a global movement of all objects towards the objects with heavier mass. The exploitation step of the algorithm is guaranteedbecause of the slow movement of the heavy masses than the lighter ones and these heavy masses correspond to good solution. Position, inertial mass, active gravitational mass, and passive gravitational mass are the four specifications of each mass in GSA and each mass offers a solution. By lapse of time the heavier mass may attract the masses and this represents the optimum solution in the search space.

Where *kbest* is the set of first *k* agents with the best fitness value and biggest mass *k*. The GSA being simple in concept can be easily implemented and has good computational efficiency. Also because of its flexibility and balanced mechanism, exploration and exploitation capabilities can be improved. By considering a higher inertia mass that causes a slower motion of agents in the search space, the search can be achieved more precisely, and by assuming a higher gravitational mass which attracts agents, the convergence can be obtained at a faster rate. It is found that the global optimum can be obtained at a faster rate as compared to other techniques by using GSA and also for unimodal high dimensional functions it has higher convergence rate. The performance of GSA for multi-modal functions is comparable to other algorithms.

C. Pattern Search Algorithm

Pattern search is a heuristically search method that can be applied when the given objective function is neither continuous nor differentiable or when we are not aware of the information (Dolan et al., 2003). It only depends on the functional value at a point of concern. However, it can be applicable to both the differentiable as well as non-differentiable function;. If the calculated value is given the improved value, then the current position value $x^{(i)}$, is increased by its perturbation value Δx_j. If the calculated value is coming worse than the current position value, then it is decreased by Δx_j and if the objective function value is unchanged, then there is no updating of the current value. Thus the exploratory search algorithm is as follows:

f_{best} is used to save the updated objective function value of the next position to move.

Put $x^{(1)} \leftarrow x^{(0)}$ and initialize $f_{best} \leftarrow f(x^{(1)})$

For each variable x_j in turn: $x^{(1)} \leftarrow (x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, \ldots\ldots, x_1^{(1)}+\Delta x_1, \ldots\ldots\, x_1^{(1)})$.

IV. RESULT AND DISCUSSION

For the performance evolution which includes robustness, efficiency and convergence of proposed firefly algorithm, researchers selected "Lena", "Goldhill", "Starfish" and "Pirate" as test images. and all are .jpg format images of size 225×225 and corresponding histograms are shown in Fig. 1.To examine the influence of hGSA-PS algorithm on multilevel thresholding problem, objective function/fitness function is Shannon entropy/Fuzzy entropy.

The segmented images/thresholding images and corresponding thresholds on histogram obtained with hGSA-PS,ACS and FA algorithms at thresholds level 2, 3, 4 and 5 is shown in from Fig 2 and Fig 3. Among these figures, we observed that segmented image visual quality is better with higher level of threshold (th = 5) in comparison with Th = 4, Th = 3 and Th = 2.

D. Comparison of other methods

i. Peak Signal to Noise Ratio (PSNR)

PSNR shows dissimilarity between threshold image and input image as a measure of visual difference of two images where the units are decibels (dB). A higher value of PSNR indicates better quality of threshold image or reconstructed image. The equation for PSNR is given in

$$PSNR \quad = 10 \times 10 \log\left(\frac{255^2}{MSE}\right)(\text{dB})$$

Table.4 show the PSNR value acquired by different algorithms where the proposed algorithm has achieved higher PSNR value in comparison with FA,CS,ACS and GSA.

ii. Misclassification error/Uniformity measure:

It is measure of error is measured by Eq. 13

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

Where T is the number of thresholds that are used to segment the image, R_j is the jth 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 and I_{min}& I_{max} are the maximum and minimum intensity of image respectively.

Table.5 demonstrate misclassification error of proposed and other techniques where the proven proposed method has lesser misclassification error and draws better visual quality.

iii. **Structural Similarity Index (SSIM):** It evaluates the visual similarity between the original image and the reconstructed image/thresholded image and is calculated with below equation

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

Table.6 show the SSIM of various methods and it shows that the proposed method SSIM is higher than other methods.

V. CONCLUSION

A hGSA-PS algorithm based multilevel image thresholding for image segmentation has been productively proposed with desired output.The proposed algorithm is tested on natural images to show the merits of algorithm. Results of the proposed method are compared with other optimization techniques such as FA,CS,ACS and GSA. It is observed that proposed algorithm has higher/maximum fitness value compared FA,CS,ACS and GSA. The PSNR value shows higher values with proposed algorithm than FA,CS,ACS and GSA and thereby draws better quality of the segmented image with proposed method. It can be concluded that proposed algorithm outperform FA,CS,ACS and GSA in all performance measuring parameters.

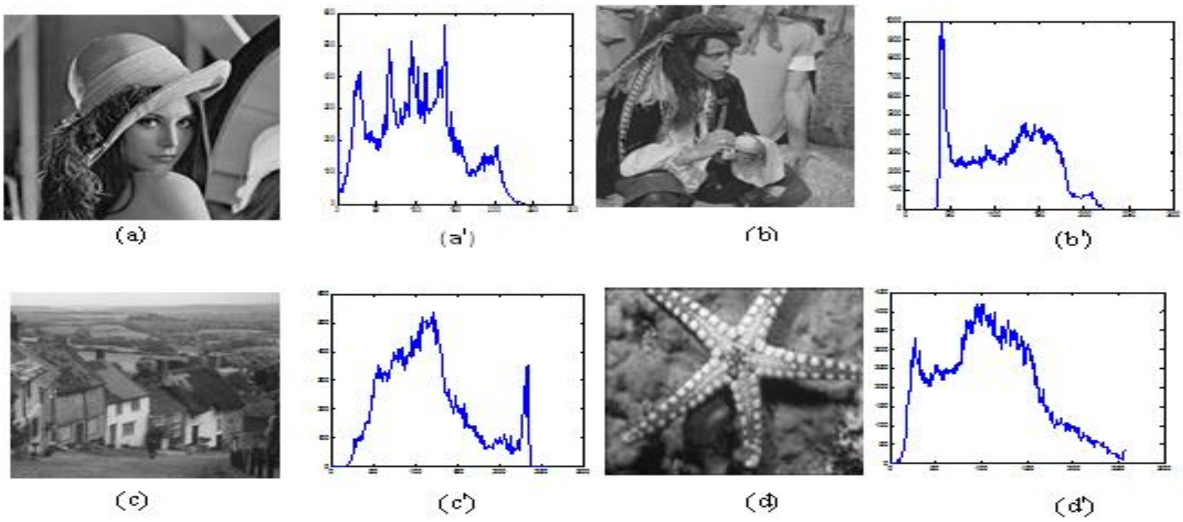

Fig. 1.Test images and corresponding histograms a) Lena b) Pirate c) Goldhill d) Starfish.

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	FA	12.7714	14.322	15.8999	17.9599	18.8063	21.3874	21.58616	24.5615
	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
	GSA	12.9798	15.1595	15.9991	17.9819	19.7827	22.4188	22.42001	25.3212
	hGSA-PS	14.8891	16.4148	17.9032	19.9899	20.8091	23.4318	23.4778	26.4588
Goldhill	FA	12.1048	13.563	15.1576	17.0985	17.8997	20.273	20.55085	23.3604
	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
	GSA	12.4712	13.601	15.2019	17.1643	17.9847	20.3038	20.43222	23.4123
	hGSA-PS	14.1923	15.651	16.239	19.2909	18.9901	22.3877	23.5191	26.4318
Pirate	FA	12.8561	14.031	16.123	17.9929	19.9677	21.8398	21.75928	24.7943
	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
	GSA	12.8901	14.124	16.1579	17.8123	19.202	21.6128	21.80182	24.7899
	hGSA-PS	14.9923	16.217	18.239	19.9272	22.3918	23.7808	23.90191	26.8043
Starfish	FA	13.0157	14.611	16.2357	18.3377	19.3096	21.7994	22.12073	25.6378
	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
	GSA	13.9282	14.9243	16.3215	18.9951	19.4078	21.8909	22.30281	25.3102
	hGSA-PS	15.0301	16.7652	17.3336	20.4001	21.4176	23.9006	24.3869	27.3677

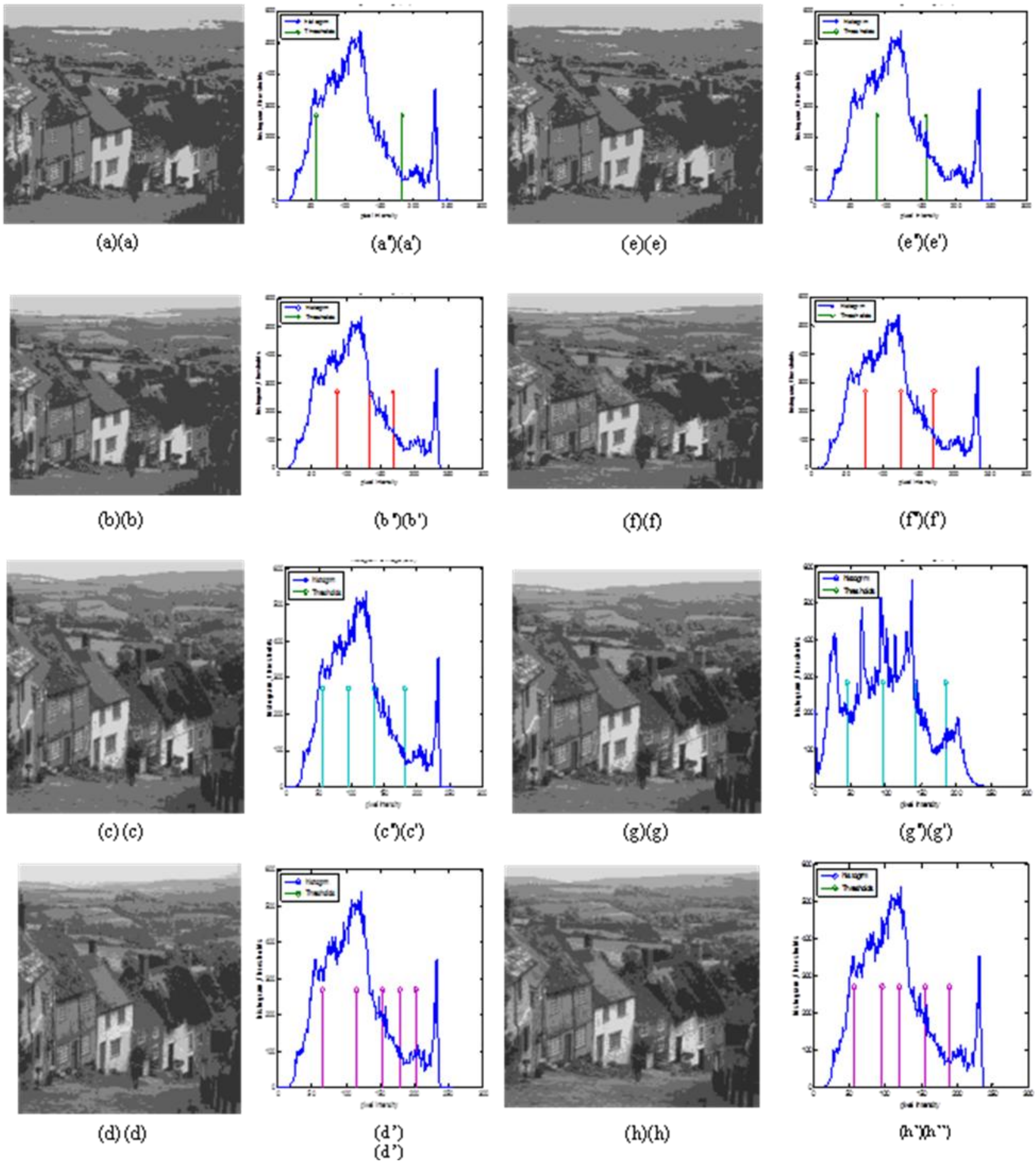

Fig. 2. Segmented images and thresholds on histogram of Goldhill image with various thresholds achieved by FA and hGSA-PS with Shannon entropy. (a)-(d) shows 2-5 level segmented images achieved by FA respectively. (a')-(d') shows 2-5 level thresholds on histogram achieved by FA respectively. (e)-(h) shows 2-5 level segmented images achieved by hGSA-PS respectively. (e')-(h') shows 2-5 level thresholds on histogram achieved by hGSA-PS respectively

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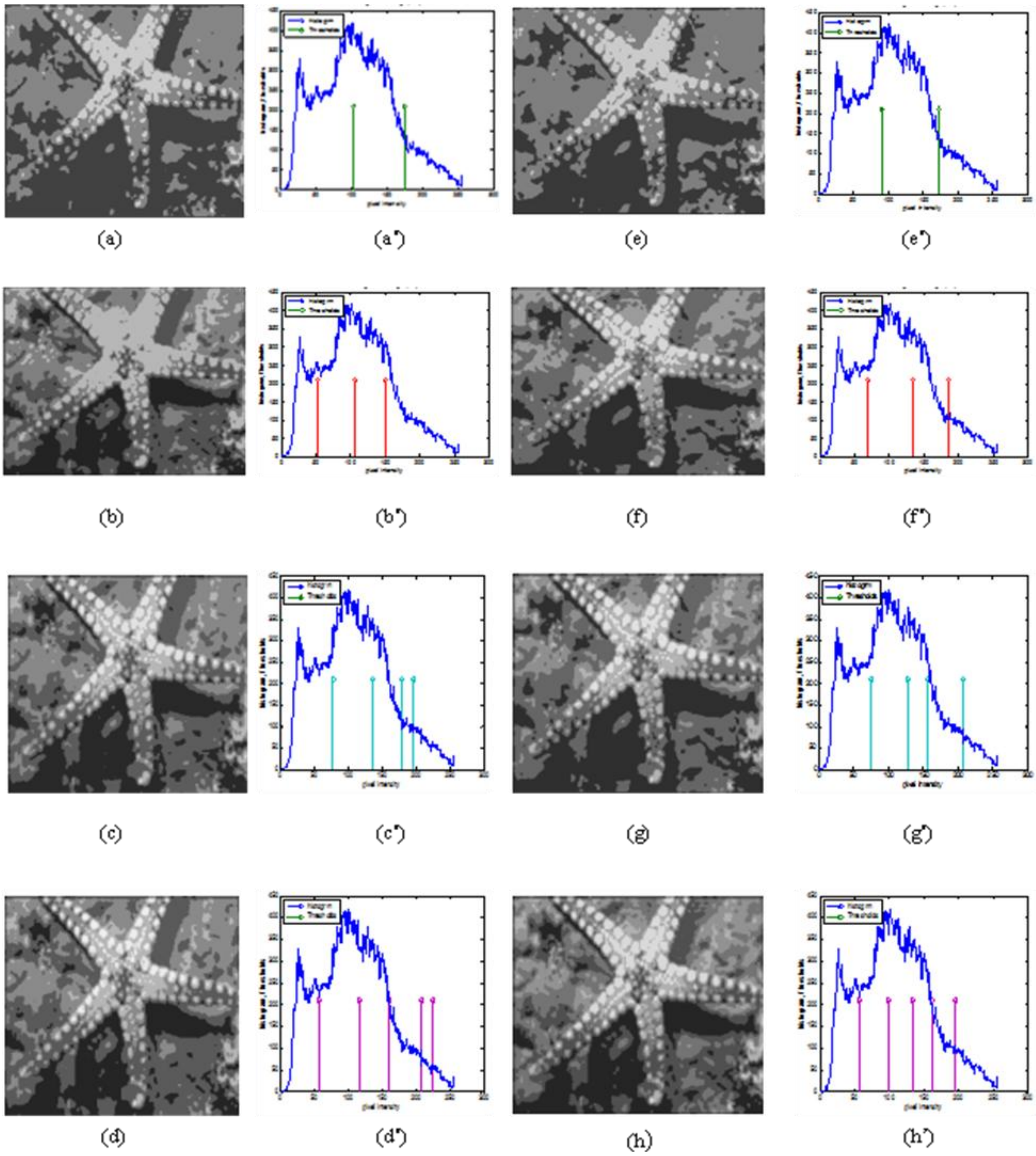

Fig. 3. Segmented images and thresholds on histogram of Starfish image with various thresholds achieved by ACS and hGSA-PS with Fuzzy entropy. (a)-(d) shows 2-5 level segmented images achieved by ACS respectively. (a')-(d') shows 2-5 level thresholds on histogram achieved by ACS respectively. (e)-(h) shows 2-5 level segmented images achieved by hGSA-PS respectively. (e')-(h') shows 2-5 level thresholds on histogram achieved by hGSA-PS respectively.

Table .2: Optimal threshold values obtained by Fuzzy entropy based evolutionary algorithms.

Im	Opt Tech	Th = 2	Th = 3	Th = 4	Th = 5
Lena	FA	55,181	78,120,170	36,119,149,193	23,61,110,169,172
	CS	78,146	63,113,162	61,101,140,183	50,93,138,169,213
	ACS	93,166	53,84,175	64,113,150,164	59,97,133,162,196
	GSA	99,123	44,121,190	30,99,140,180	51,74,112,151,190
	hGSA-PS	76,149	51,112,159	50,93,149,175	37,75,113,147,189
Goldhill	FA	99,167	81,141,192	61,129,159,198	47,87,124,161,214
	CS	89,115	82,139,190	66,121,167,198	48,87,145,189,213
	ACS	91,190	80,152,189	65,123,156,180	51,88,132,176,223
	GSA	87,172	78,149,188	43,98,134,156	54,76,132,187,214
	hGSA-PS	77,171	72,133,167	65,68,156,187	56,88,127,167,229
Pirate	FA	74,200	54,142,179	87,113,162,174	65,119,151,179,216
	CS	110,179	93,135,179	78,119,148,181	75,108,126,151,181
	ACS	110,167	49,124,163	50,85,155,185	50,92,126,182,231
	GSA	99,186	33,125,187	52,84,164,188	45,98,154,182,221
	hGSA-PS	96,157	81,141,192	73,98,141,188	57,92,144,168,198
Starfish	FA	76,199	44,128,213	56,123,172,218	25,75,108,173,219
	CS	88,169	70,125,86	62,108,156,203	50,99,135,175,218
	ACS	95,162	60,165,213	62,88,144,222	24,66,110,172,206
	GSA	78,156	65,154,220	61,81,121,223	45,98,126,156, 231
	hGSA-PS	81,161	63,128,185	56,123,153,208	44,80,128,167,208

Table 3: Optimal threshold values obtained by Shannon entropy .

Im	Opt Tech	Th = 2	Th = 3	Th = 4	Th = 5
Lena	FA	75,154	45,115,170	49,99,131,195	11,41,70,1022,157
	CS	88,156	77,119,174	49,93,156,194	49,91,129,161,194
	ACS	87,156	75,125,171	59,100,145,194	56,95,119,155,189
	GSA	86,149	86,135,168	56,94,134,181	65,115,152,178,201
	hGSA-PS	82,123	53,119,176	45,97,136,198	44,80,125,152,204
Goldhill	FA	111,180	85,131,180	74,110,146,181	65,95,123,152,181
	CS	98,154	76,120,179	73,84,158,177	73,98,125,179,200
	ACS	101,178	76,122,186	69,112,155,183	60,93,123,155,190
	GSA	12,180	76,127	82,106,148,183	64,97,132,163,191
	hGSA-PS	101,184	50,112,181	65,134,157,197	49,98,109,124,174
Pirate	FA	97,164	73,109,167	48,103,138,162	106,132,164,188,212
	CS	71,175	74,133,190	59,121,167,206	53,87,127,174,221
	ACS	90,172	69,133,185	75,127,157,206	56,98,132,161,195
	GSA	102,174	52,106,149	77,136,179,196	56,116,160,209,225
	hGSA-PS	110,179	64,128,198	49,116,152,209	48,86,125,158,201
Starfish	FA	102,174	52,106,149	77,136,179,196	56,116,160,209,225
	CS	57,221	72,133,167	65,68,156,187	56,88,127,167,229
	ACS	86,171	72,131,190	62,109,156,199	41,85,125,171,217
	GSA	93,180	81,131,222	59,93,178,227	63,148,162,195,224
	hGSA-PS	72,189	58,145,209	49,105,153,223	4,96,141,181,225

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	FA	28.8263	28.8438	29.8227	29.6273	30.0818	29.745	31.7253	30.9163
	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
	GSA	29.5932	29.465	29.9744	29.99	29.4447	29.7922	29.5668	30.5001
	hGSA-PS	31.9691	31.7459	32.9991	32.7019	32.8591	32.9102	34.2209	34.9956
Goldhill	FA	29.2461	29.1103	29.4845	29.5282	30.798	30.2903	31.46021	31.481
	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
	GSA	29.6001	29.51119	29.8909	29.9101	31.1833	30.6811	31.8292	31.7282
	hGSA-PS	32.7829	32.63933	32.9001	32.9912	33.2345	32.7902	34.9011	34.8272
Pirate	FA	29.3865	28.7525	29.813	29.8614	30.9543	31.2954	32.25837	32.4861
	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
	GSA	29.902	29.5912	30.6991	31.2345	31.9788	31.5673	32.6789	32.8345
	hGSA-PS	32.1039	32.9857	33.2919	33.4028	33.9993	34.393	35.3939	35.4839
Starfish	FA	28.729	28.70678	29.5402	29.2359	29.7837	29.5676	30.74565	30.5047
	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
	GSA	28.6393	28.78282	29.5859	29.921	30.1273	30.902	30.5747	30.8959
	hGSA-PS	31.809	31.9808	32.4495	32.6293	32.8489	32.9828	33.7747	33.8127

Table 5: 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	FA	0.95957	0.948264	0.93835	0.946852	0.86788	0.90292	0.748263	0.72331
	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
	GSA	0.9594	0.947001	0.91002	0.93321	0.86012	0.89393	0.747222	0.71553
	hGSA-PS	0.93634	0.910098	0.89885	0.869393	0.82848	0.81475	0.64839	0.60184
Goldhill	FA	0.97102	0.930716	0.92363	0.909869	0.79694	0.72377	0.68383	0.61792
	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
	GSA	0.95123	0.93001	0.90272	0.892727	0.79363	0.73393	0.65453	0.63349
	hGSA-PS	0.93211	0.89848	0.87287	0.853731	0.75364	0.67373	0.61633	0.57384
Pirate	FA	0.95698	0.930858	0.94346	0.933864	0.86343	0.89656	0.811681	0.83505
	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
	GSA	0.95555	0.928383	0.94384	0.932929	0.86848	0.88383	0.81282	0.81257
	hGSA-PS	0.92474	0.907272	0.91482	0.900837	0.83939	0.85383	0.78488	0.76085
Starfish	FA	0.96416	0.943572	0.92528	0.915473	0.91566	0.90222	0.800406	0.73047
	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
	GSA	0.96384	0.94838	0.92303	0.913933	0.91392	0.90089	0.794433	0.7299
	hGSA-PS	0.93374	0.918382	0.90847	0.886773	0.86475	0.84384	0.74094	0.68773

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Table 6: 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	FA	0.70656	0.69508	0.77541	0.750278	0.798	0.78276	0.83524	0.82797
	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
	GSA	0.7694	0.75292	0.79122	0.784412	0.80001	0.81394	0.838383	0.79991
	hGSA-PS	0.82948	0.80494	0.84474	0.838373	0.85934	0.84984	0.87871	0.86009
Goldhill	FA	0.65587	0.64551	0.74153	0.694545	0.78699	0.73222	0.822033	0.80963
	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
	GSA	0.68383	0.68393	0.79886	0.739292	0.80828	0.76848	0.858585	0.83838
	hGSA-PS	0.78303	0.76908	0.81991	0.79449	0.83838	0.80283	0.89383	0.86848
Pirate	FA	0.67066	0.611312	0.75469	0.720464	0.82161	0.81966	0.87572	0.84312
	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
	GSA	0.69838	0.68399	0.79939	0.779292	0.86394	0.82199	0.88333	0.86374
	hGSA-PS	0.76448	0.747847	0.83748	0.817484	0.88886	0.87265	0.89963	0.884647
Starfish	FA	0.58447	0.525031	0.68289	0.665436	0.72191	0.71928	0.78991	0.77247
	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
	GSA	0.60519	0.58999	0.69193	0.679091	0.74123	0.7302	0.795432	0.77644
	hGSA-PS	0.66595	0.638282	0.74172	0.737872	0.83094	0.81475	0.88746	0.87737

REFERENCES

1. Agrawal. S, R. Panda, S. Bhuyan, B.K. Panigrahi, “Tsallis entropy based optimal multilevel thresholding using cuckoo search algorithm”, Swarm and Evolutionary Computation, Vol. 11 pp. 16–30, 2013.
2. Ayala. H, F. Santos, V. Mariani and L. Coelho, “Image thresholding segmentation based on a novel beta differential evolution approach”, Expert Systems with Applications, Vol. 42, pp. 2136–2142, 2015.
3. Bhandari. A. K, A. Kumar, G. K. Singh, "Tsallis entropy based multilevel thresholding for colored satellite image segmentation using evolutionary algorithms”, Expert Systems With Applications, Vol. 42, pp. 8707–8730, 2015.
4. Bhandari. A. K, A. Kumar, G. K. Singh, " Modified artificial bee colony based computationally efficient multilevel thresholding for satellite image segmentation using Kapur’s, Otsu and Tsallis functions”, Expert Systems With Applications, Vol. 42, pp. 1573–1601, 2015.
5. Luca. A, S. Termini, A definition of a non-probabilistic entropy in the setting of fuzzy sets theory, Inf. Control 20 (1972) 301–312.
6. Horng. M and T. Jiang, “Multilevel Image Thresholding Selection based on the Firefly Algorithm”, Symposia and Workshops on Ubiquitous, Autonomic and Trusted Computing, pp. 58–63, 2010.
7. Hussein. W. A, S. Sahran , S. Abdullah, “A fast scheme for multilevel thresholding base d on a modifie d b ees algorithm”, Knowledge-Based Systems, Vol. 101, pp. 114–134, 2016.
8. Kapur. J. N, P.K.Sahoo, A.K.C Wong, A new method for gray-level picture thresholding using the entropy of the histogram”, Computer Vision Graphics Image Process. 29 (1985) 273 – 285.
9. Li. Y, L. Jiao, R. Shang, R. Stolkin, “Dynamic-context cooperative quantum-behaved particle swarm optimization based on multilevel thresholding applied to medical image segmentation”, Information Sciences, Vol. 294, pp. 408–422, 2015.
10. Mbuyamba. M, J. Cruz-Duarte , J. Avina-Cervantes, C. Correa-Cely, D. Lindner, and C. Chalopin, “Active contours driven by Cuckoo Search strategy for brain tumour images segmentation”, Expert Systems With Applications, Vol. 56, pp. 59–68, 2016.
11. Otsu. N, “A threshold selection from gray level histograms” IEEE Transactions on System, Man and Cybernetics 66, 1979.
12. Ouadfel. S and A. Taleb-Ahmed, “Social spiders optimization and flower pollination algorithm for multilevel image thresholding: A performance study”, Expert Systems with Applications, Vol. 55 pp. 566–584, 2016.
13. Penga. H, J. Wangb, M. Pérez-Jiménezc, “Optimal multi-level thresholding with membrane computing”, Digital Signal Processing, Vol. 37, pp. 53–64, 2015.