MULTILEVEL THRESHOLDING FOR COLOR IMAGE SEGMENTATION USING OPTIMIZATION ALGORITHM

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***Abstract*—Satellite color image segmentation could be a difficult surroundings is a due to the presence of weakly correlated and ambiguous multiple regions of interest. Many algorithms are developed to get optimum threshold values for segmenting satellite images with efficiency in their quality and blurred regions of image. Their complete search nature makes them computationally expensive when extended from bilevel thresholding to multilevel thresholding. In this work, a computationally efficient image segmentation algorithm is used to select the threshold values that resulted in improved segmentation quality with an expense of computational time. The performance of the efficient harmony search algorithm is compared with two different objective functions for threshold optimization. Experimental results are validated by evaluating PSNR, STD, MEAN, MSE, best fitness and elapsed time for all the set of benchmark images. The algorithm evolved to be most promising and computationally efficient for segmenting satellite color images achieve stable global optimum thresholds. The experiments results encourages related researches in computer vision, remote sensing and image processing applications.**

***Keywords*—Image segmentation, Otsu's, Kapur's entropy, Optimal threshold, Optimization algorithm**

I. INTRODUCTION

Image segmentation is the method of partitioning a digital image into multiple segments called set of pixels or super pixels. The foremost goal of segmentation is to change or modify the illustration of an image into one thing that is easier to investigate. There are several segmentation methods like segmentation supported fuzzy cluster algorithms, fuzzy c-means and mean shift analysis. Among all the prevailing segmentation techniques, the image thresholding technique (Shilpa Suresh et al., 2016) could be a most well liked image segmentation technique attributable to its simplicity, strength and accuracy that converts a grey level image into a binary image. The key of this technique is to pick out the threshold value or the values when multiple levels are chosen. Many methods are used in image segmentation including the maximum entropy technique, Otsu's technique (maximum variance), and k-means cluster.

The threshold-based methodology may be a common segmentation theme, which might be thought to be the component classification. A feature value like grey level is related to every component. The value is compared to the threshold to classify a pixel into an object or the background. Usually image segmentation techniques is classified as bilevel thresholding and multilevel thresholding in accordance with the quantity of thresholds (Bhandari .A.K et al.,2016). The former selects only one threshold that classifies the pixels into two categories, whereas the latter determines multiple thresholds that divide the pixels into many categories. In some cases, the threshold is obtained automatically on the premise of the histogram of images for some simple images without noise or with low noise. An equivalent approaches are utilized in color images for segmentation (Rajinikantha. V et al., 2015) using multiband channel R,G,B (Red, Green, Blue). The nature of the image histogram could also be unimodal or multimodal, specified choice of the acceptable threshold value is less obvious. The fundamental limitation of this method is that it fails to exploit all the useful information provided by the image. Therefore, the auto selection of robust optimum threshold has remained a challenge for complex image segmentation. As a replacement trend, multi-objective optimization algorithms are utilized in drawback formulation for image segmentation. Multi-objective optimization additionally referred to as Pareto optimization is an extension of optimization with single objective. Image segmentation drawback is handled as a multi objective optimization. The multi-objective optimization algorithms based on meta heuristic techniques are suitable method to deal with natural image segmentation problem which contains multiple objectives like maximization of inter-region compactness and minimization of intra-region separation.

This paper is organized as follows: in Section II, the preliminaries of the multilevel thresholding and optimization are introduced. The framework of the proposed multilevel theresholding with optimization is described in Section III. In section IV, the experimental results and discussions are shown. The conclusions of the work is presented in section V.

II. LITERATURE SURVEY

Thresholding methodology separates objects from background and discriminate objects from objects that have distinct gray levels. Thresholding are classified as global and local thresholding methods. When the threshold is based on only one value for entire image, then it is said to be global thresholding. (Shilpa Suresh et al., 2016) Local thresholding techniques partition the given image into a number of sub images and threshold value is determined locally for each sub image. Thresholding is based on the clip level or a threshold value to turn a gray-scale image into a binary image. There is also a balanced histogram thresholding.

The aim of this technique is to pick the threshold value or values when multiple levels are selected. Thresholding can further be classified as bilevel or multilevel thresholding. The automatic multilevel thresholding called as automatic thresholding criterion to determine automatically the number of classes by which gray levels can be classified and their threshold values. (Rajinikantha. V et al., 2015) The same approach for thresholding is extended to color images also.

Rosin et al.(2001) presented a bilevel thresholding to find an intensity value that makes the foreground and background object of the image distinguishable.

In images, it is difficult to clearly distinguish between the background and objects of interest . Bi-level image thresholding proves to be inefficient and thus forced to move for a multilevel image thresholding scheme (Sparea .S et al.2016). Multilevel thresholding will find more than one gray level threshold value so as to distinguish the objects of interest from the image. The same can be extended to color images also where have to process R, G, B (Tahir Saga et al.,2015) channels.

A. *OBJECTIVE FUNCTIONS*

Otsu N. et al. (1979) proposed Otsu method otherwise referred as between-class variance technique, which is a non- parametric segmentation technique that aims to maximize the between-class (inter-class) variance thereby minimizing the among class variance measure between the pixels in each class. It is based on the probability distribution of the intensity values that is comprising a foreground and a background region (Kapur .J. N et al.,1985). Tsai W. (1985) proposed tsallis entropy by Constantio Tsallis is additionally referred to as Boltzmann-Gibbs entropy measure. It is used to measure a non-extensive system governed by a entropy and used for segmenting grayscale and color images. (Agrawal .S et al.,2013)

B. OPTIMIZATION ALGORITHMS

The genetic algorithm method is quicker as a result of its parallel search techniques that emulate natural genetic operations. The genetic algorithm methods (Manikandan .S et al.,2014) are used successfully to solve complex nonlinear optimization problems. The differential evolution (DE) algorithm is proposed by Stornand Price, has been applied to many multilevel thresholding and image processing issues since it has gained a wider range of acceptance and popularity (Soham Sarkar et al.,2016). There are three main operators in DE algorithm which are mutation, crossover and selection.

WDO (Wind Driven Optimization) is a modern nature-inspired global optimization method based on atmospheric motion (Ashish Kumar Bhandari et al., 2014). It is revealed that WDO is easy to execute and extremely effective in finding multidimensional numerical optimization issues .

PSO (Particle Swarm Optimization) is a common heuristic technique used for global optimization (Sathya .P et al., 2010) that comes from considering swarm of animals in nature. Two basic updating equations for particle position first is velocity updating equation, and other is position updating equation. Global exploration and local exploration feature during optimization process is the key feature of PSO (Akay, 2013).

DPSO (Darwinian Particle Swarm Optimization) is one such approach that depends upon the Darwin's natural selection principle to induce out of local traps (Kayalvizhi R. et al., 2010). DPSO approach have more than one swarm at a time that performs individually like a single swarm governed by certain rules.

CS (Cuckoo search) algorithm is an elitist search algorithm based on population (Sparea .S et al,2016). It is also a meta-heuristic optimization algorithm. Cuckoo birds are most popular because of their attractive voice and fascinating singing style. Their reproduction policy is also one of the most aggressive among the birds. Cuckoos can engage indirect conflict with the host birds . The host bird can either gets rid of the egg away or simply abandon the nest and build a complex new nest. (Shilpa Suresh et al.,2016).

ABC (Artificial Bee Colony) optimization algorithm was proposed by Dervis Karaboga, inspired by the intelligent behavior of honey bees in seek for nectar. It is a population based search procedure in which honey bees seek for the food position throughout the solution space to find the one with the highest nectar (Zhang .Y, & Wu .L. 2011). The bees engaged for this searching method are divided into three categories: 1) Employer bees, 2) Onlooker bees and 3) Scout bees

III. METHODOLOGY

In satellite image segmentation, the satellite image is partitioned into distinct classes and each of these classes have different quality of segmentation and the image is not clear by their regions. To overcome this variation in quality of the images and blurred regions of the images, the multilevel thresholding technique with an optimization algorithm is used, so as to select an optimal threshold value in image segmentation. Selecting the optimal threshold until the threshold has no change is an important in the segmentation. The aim of this work is to improve the quality and accuracy of segmentation of images using multilevel thresholding techniques. This technique optimizes the threshold values using an optimization algorithm with an objective function. Figure 1 shows block diagram of the multilevel thresholding method.

A. INPUT IMAGE

Image processing is a processing of images using mathematical operations, where the input is an image, a series of images, or a video, like a a photograph or video frame. In this work, the input image is given as the satellite images to find the optimal threshold values to perform the segmentation. The images for this experiment are taken from the image database. (http://www.imageprocessingplace.com/root_files_V3/image_databases.htm)

B. PREPROCESSING

Preprocessing is the first phase of image analysis. The preprocessing step includes the removal of noise and suppression of artifacts . This work uses the histogram equalization as a preprocessing to

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remove noise from the satellite images while not considerably reducing the sharpness of the image.

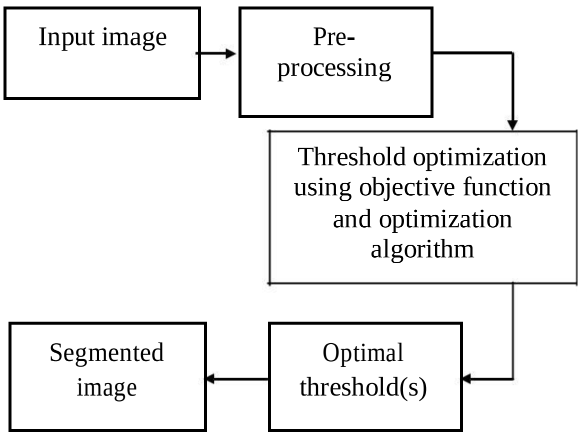

Fig 1. Block diagram of the multilevel thresholding method

C. MULTILEVEL THRESHOLDING (MT)

Thresholding is a method in which the pixels of a gray scale image are divided in sets or classes depending on their intensity level ( ). For this classification it is necessary to select a threshold value (th) and follow the simple rule of

$$c_1 \leftarrow p \quad if \quad 0 \le p < th \qquad (1)$$

$$c_2 \leftarrow p \quad if \quad th \le p < L-1 \qquad (2)$$

where is one of the × pixels of the gray scale image I_g that can be represented in gray scale levels = {0, 1, 2, . . . , −1}. c_1 and c_2 are the classes in which the pixel can be located, while th is the threshold. The rule in (5) corresponds to a bilevel thresholding and can be easily extended for multiple sets:

$$c_1 \leftarrow p \quad if \quad 0 \le p < th_1 \qquad (3)$$

$$c_2 \leftarrow p \quad if \quad th_1 \le p < th_2 \qquad (4)$$

$$c_i \leftarrow p \quad if \quad th_i \le p < th_{i+1} \qquad (5)$$

$$c_n \leftarrow p \quad if \quad th_n \le p < th_{L-1} \qquad (6)$$

where $\{ th_1, th_2, \ldots, th_i, th_{i+1}, th_k \}$ represent different thresholds.

The problem for both bilevel and MT is to select the th values that correctly identify the classes. Although, Otsu's and Kapur's methods are well-known approaches for determining such values, both propose a different objective function which must be maximized in order to find optimal threshold values.

D. OBJECTIVE FUNCTIONS

i. BETWEEN-CLASS VARIANCE (OTSU'S METHOD)

This is a nonparametric technique for thresholding that employs the maximum variance value of the different classes as a criterion to segment the image. Taking the intensity levels from a gray scale image or from each component of a RGB (red, green, and blue) image, the probability distribution of the intensity values is computed

$$ph_i^c = \frac{h_i^c}{NP} \qquad (7)$$

$$\sum_{i=1}^{NP} ph_i^c = 1 \qquad (8)$$

where i is a specific intensity level (0 ≤ ≤ − 1), c is the component of the image which depends if the image is grayscale or RGB, if c =1,2,3 RGB image and if c =1 grayscale image, whereas NP is the total number of pixels in the image. h_c^i (histogram) is the number of pixels that corresponds to the i intensity level in c . The histogram is normalized within a probability distribution ph_c^i .

Otsu's method is applied for a single component of an image. In case of RGB images, it is necessary to apply separately in R,G,B component of the images. The previous description of such bilevel method can be extended for the identification of multiple thresholds. Considering k thresholds, it is possible separate the original image into k classes then it is necessary to compute the k variances and their respective elements.

ii. ENTROPY CRITERION METHOD (KAPUR'S METHOD)

The entropy method is also nonparametric method that is used to determine the optimal threshold values. It is based on the entropy and the probability distribution of the image histogram. The method aims to find the optimal th that maximizes the overall entropy. The entropy of an image measures the compactness and separability among classes. In this sense, when the optimal th value appropriately separates the classes, the entropy has the maximu m value.

$$J(th) = H_c^1 + H_2^c \qquad (9)$$

where H_1 and H_2 are entropies, c is the component of the image if c =1,2,3 RGB image and if c =1 grayscale image. The entropy-based approach can be extended for multiple threshold values for such a case, it is necessary to divide the image into k classes using the similar number of thresholds.

E. OPTIMAL THRESHOLD SELECTION USING HARMONY SEARCH ALGORITHM

To optimize the threshold values harmony search optimization algorithm is used. This harmony search algorithm is combined with the two different objective functions Otsu function (between class variance) and Kapur function (entropy criterion), to perform segmentation on the color satellite images . The harmony search algorithm (HSA) is an evolutionary optimization algorithm that relies on the metaphor of the improvisation method that occurs when a musician searches for a better state of harmony. The convergence for the HSA is quicker than other algorithms that attract more attention. The proposed algorithm takes random samples from a possible search area within the image his togram. Such samples build each harmony (candidate solution) within the HSA context, whereas its quality is evaluated considering the objective function that's used by the Otsu's or the Kapur's technique. By these objective values, the set of candidate solutions are evolved using the HSA operators until the optimum solution is found. The approach generates a multilevel segmentation algorithm which can effectively identify the threshold values of a satellite image within a reduced range of iterations. In HSA, every solution is named a "harmony" and is represented by an n dimension real vector. An initial population of harmony vectors are randomly generated and stored within a harmony memory (HM). A new candidate harmony is therefore generated from the elements in the HM by using a memory consideration operation either by a random reinitialization or a pitch adjustment operation. Finally, the HM is updated by comparing the new candidate harmony and the worst harmony vector in the HM. The worst harmony vector is replaced by the new candidate vector when the latter delivers a better solution in the HM. The above process is repeated until there is no change in the fitness value. The basic HS algorithm consists of three main phases HM initialization, improvisation of new harmony vectors, and updating the HM.

The steps in the HS algorithm are as follows:

1: Read the image and if it is RGB separate it into , and .

If is gray scale store it into Gr.
= 1, 2, 3 for RGB images or = 1 for gray scale images.

2: Obtain histograms for RGB images h^R, h^G, h^B and for gray scale images h^{Gr}.

3: Calculate the probability distribution and obtain the histograms.

4: Initialize the HSA parameters: HMS, , HMCR, PAR, BW, NI, and the limits and .

5: Initialize a HM x_i^c of HMS random particles with dimensions.

6: Evaluate each element of HM in the objective function (HM) or depending on the thresholding method (Otsu or Kapur).

7: Improvise a new harmony and update the HM with the new value.

8: If NI is completed or the stop criteria is satisfied. Otherwise repeat the steps from evaluation.

9: Select the harmony that has the best x_{best}^c best objective function value.

10: Apply the thresholds values contained in x_{best}^c best to the image .

Each harmony (candidate s olution) uses different elements as decision variables within the optimization algorithm. Such decision variables represent a different threshold point th that is used for the segmentation where HMS is the size of the harmony memory, the harmony memory consideration rate (HMCR), the pitch adjusting rate (PAR), the distance bandwidth (BW), and the number of improvisations (NI), x_i is the i^{th} element of HM, and = 1, 2, 3 is set for RGB images while = 1 is chosen for gray scale images. The boundaries of the search space are set to = 0 and = 255, which correspond to image intensity levels.

F. SEGMENTATED IMAGE

The given satellite color image is divided into regions or categories that correspond to different objects or parts of objects. The output image is segmented based on the RGB color components to enhance the quality of satellite images and the images are validated based on the efficiency of the proposed technique related to accuracy, speed, and robustness .

IV. EXPERIM ENTA L RESULTS

The performance has been evaluated in multilevel thresholding using harmony search algorithm with two objective functions Otsu and Kapur. The evaluation metrics are STD (Standard Deviation), PSNR (Peak to Signal Ratio) and RMSE (Root Mean Square Error). The standard deviation is used to evaluate the stability and consistency. The STD represents a measure about how the data are dispersed. The algorithm becomes a lot of instable as the STD value increases .

$$STD = \sum_{I=1}^{NI} \sqrt{\frac{(bf_1 - av)}{Ru}} \qquad (10)$$

where, bf_i is the best fitness of the th iteration

av is the average value of bf

Ru is the number of total executions

An index of quality, the peak-to signal ratio (PSNR) is used to assess the similarity of the segmented image against a reference image (original image).

$$PSNR = 20 \log_{10}\left(\frac{255}{RMSE}\right) \qquad (11)$$

$$RSME = \sqrt{\frac{\sum_{i=1}^{r}\sum_{j=1}^{c}\left(I_{0^c}(i,j) - I_{th^c}(i,j)\right)}{r \times c}} \qquad (12)$$

Where, $I_0{}^c$ is the original image, $I_{th}{}^c$ is the segmented image, $C=1$ for gray scale, and $C=3$ for RGB images, whereas r, c are the total number of rows and columns of the image.

The results are tested with the set of benchmark images based on the threshold level, intensity values, standard deviation, mean, PSNR, best fitness and elapsed time. The results are compared with the two objective functions Otsu and Kapur. The Otsu's function with harmonic search is applied over the complete set of benchmark images, whereas the results are tabulated in Table 1. Such results present the best threshold values after testing the proposed method with four different threshold points $th = 2,3,4,5$. It is evident that the PSNR and STD values increase their magnitude as the number of threshold points also increases.

The performance of HSMA after considering the entropy function as objective function over the entire set of benchmark images is presented in Table 2. The values listed are PSNR, STD and the best threshold values of the optimized fitness value. The same test procedure that was previously applied to the Otsu's method is used with the Kapur's method, also considering the same stop criterion and a similar HSA parameter configuration. Four different threshold points have been employed th = 2, 3, 4, 5.

TABLE 1. Results after applying the HSMA with Otsu's to the set of benchmark images

IMAGES	K	INTENSITY_ OTSU	STDR_ OTSU	MEANR_ OTSU	PSNRV_ OTSU	BEST_FIT_ OTSU	ELAPSED TIME (seconds)
SAT 3	2	97	0.0954	659.7980	29.3845	659.8291	4.400892
	3	70 125	2.2255	861.2421	30.4803	861.7082	7.164294
	4	64 98 151	3.2030	933.0932	31.4575	933.8612	7.349242
	5	54 74 105 157	1.4071	966.3332	32.1321	966.7838	10.177648
SAT 4	2	84	2.1150e-11	536.2697	28.2796	536.2697	5.427769
	3	61 101	0.3352	704.8520	29.0085	704.9069	4.709862
	4	56 85 122	7.0309	776.1720	30.2395	778.6391	6.521727
	5	53 77 101 136	4.2540	808.0265	31.0019	809.5535	9.147471
SAT5	2	79	0.0099	1.2684e+03	28.5166	1.2684e+03	4.249187
	3	64 125	0.1771	1.5815e+03	31.1521	1.5815e+03	5.115726
	4	58 101 154	1.9233	1.6861e+03	32.3916	1.6865e+03	5.973392
	5	51 82 115 164	2.4246	1.7287e+03	32.7030	1.7294e+03	9.724430
SAT 2	2	129	0.0711	4.3804e+03	29.8004	4.3805e+03	4.753588
	3	75 157	1.5083	4.9293e+03	31.6790	4.9296e+03	4.811939
	4	57 111 175	3.6173	5.1207e+03	32.6978	5.1215e+03	5.780058
	5	47 86 131 184	2.7352	5.1920e+03	33.1636	5.1925e+03	18.688480
SAT 1	2	132	3.2294e-11	2.3663e+03	29.0903	2.3663e+03	4.072631
	3	99 163	4.2816	2.7354e+03	30.5621	2.7362e+03	5.019996
	4	82 133 178	2.9052	2.8667e+03	31.3962	2.8670e+03	5.247796
	5	71 113 152 186	4.8570	2.9258e+03	31.9134	2.9270e+03	12.164375

Fig. 2. Original image

TABLE 2. Results after applying HSMA with Kapur's to the set of benchmark images

IMAGES	K	INTENSITY_KAPUR	STDR_ KAPUR	MEANR_ KAPUR	PSNRV_ KAPUR	BEST_FIT_ KAPUR	ELAPSED TIME (seconds)
SAT 3	2	140	0.0132	12.7920	29.6793	12.7969	5.820949
	3	99 169	0.0545	17.9493	30.3701	17.9579	5.730180
	4	91 141 194	0.0948	22.5350	30.6664	22.5565	7.912624
	5	70 111 154 201	0.0451	26.6106	31.8649	26.6287	17.294528
SAT 4	2	145	0.0089	12.4491	29.2831	12.4517	5.815316
	3	112 175	0.0343	17.5369	29.8280	17.5575	5.464888
	4	84 135 189	0.0621	22.1758	30.9907	22.2000	7.169946
	5	60 104 147 194	0.0927	26.4206	33.6912	26.4490	21.617341
SAT 5	2	146	0.0167	12.8354	29.6970	12.8428	5.459377
	3	99 167	0.0205	17.9093	31.0295	17.9171	6.405742
	4	82 134 184	0.0304	22.3791	32.0992	22.3978	12.176991
	5	57 103 146 190	0.0927	26.6045	33.4249	26.6306	28.261742
SAT 2	2	106	0.0146	13.2073	29.6325	13.2113	5.172426
	3	93 167	0.0248	18.2019	31.2437	18.2120	9.662989
	4	68 127 188	0.0590	22.8340	32.5922	22.8491	11.057011
	5	55 101 147 194	0.0615	27.1293	33.2196	27.1525	24.520970
SAT 1	2	125	0.0088	13.2836	29.0975	13.2853	5.595499
	3	86 154	0.0252	18.2324	30.5211	18.2391	6.638517
	4	38 100 161	0.0416	22.6895	31.2507	22.6989	8.093232
	5	38 99 159 220	0.0673	27.1130	34.5597	27.1295	9.106919

Fig 3. Segmented image using Otsu's function

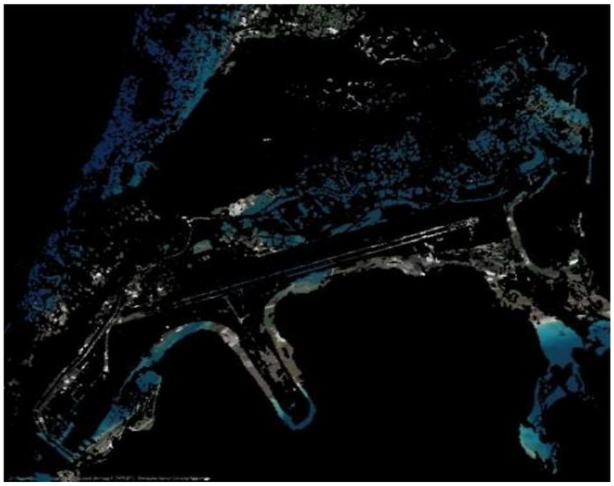

Fig 4. Segmented image using Kapur's function

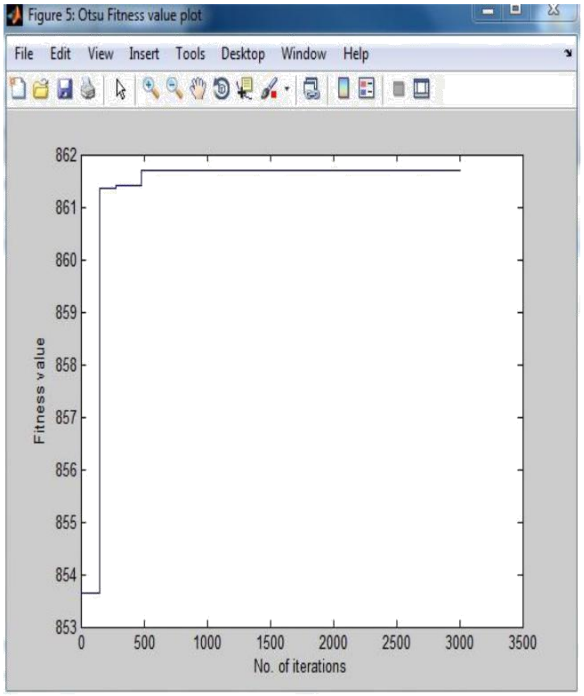

Fig 5. Otsu fitness value plot for th =2

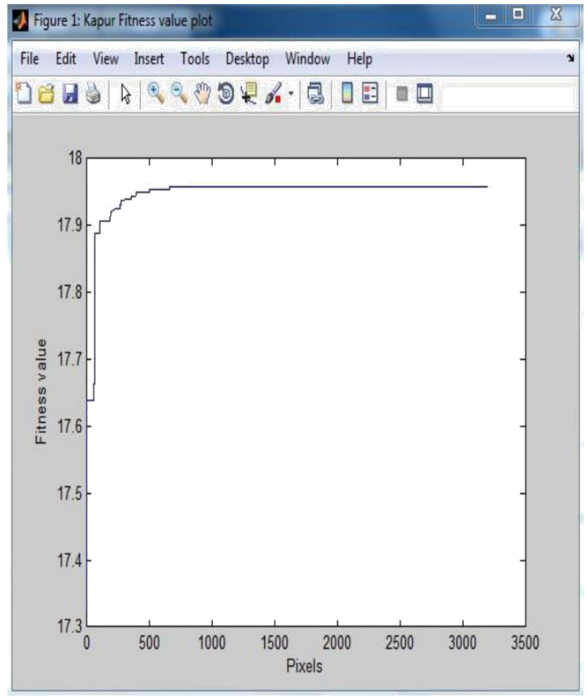

Fig 7. Kapur fitness value plot for th =2

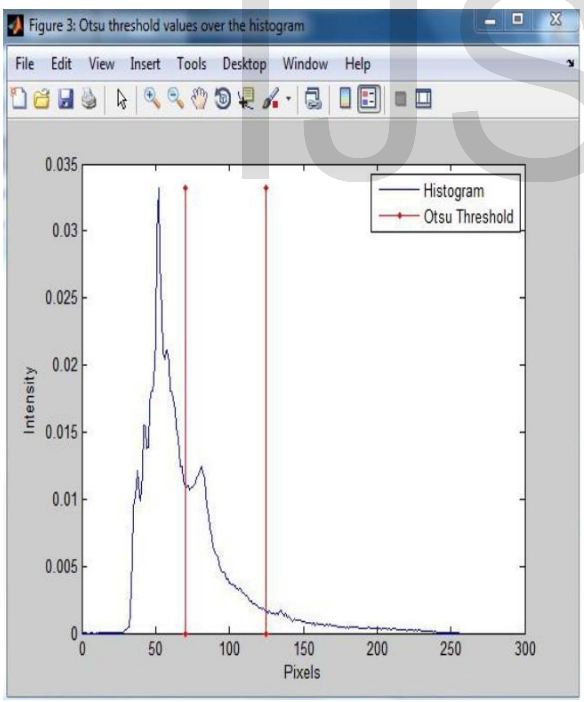

Fig 6. Otsu threshold values over the histogram for th =2

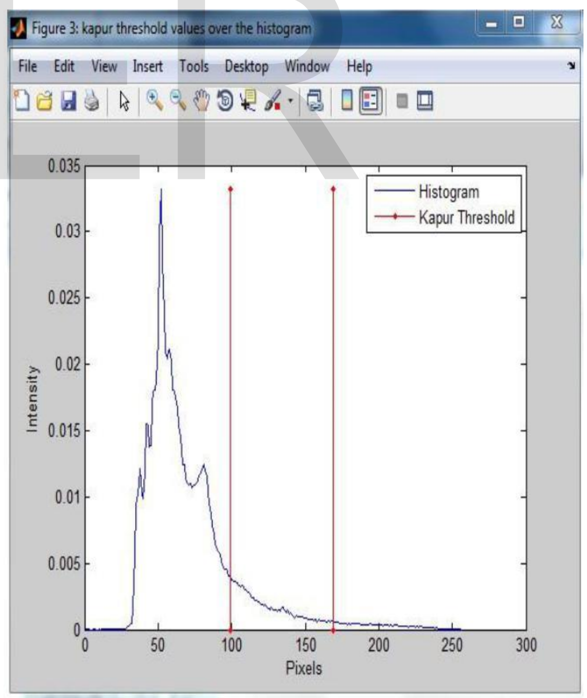

Fig 8. Kapur threshold values over the histogram for th =2

From the results of both Otsu's and Kapur's methods, it is possible to appreciate that the HSMA converges (stabilizes) after a determined number of iterations depending on the threshold (th) value. For experimental purposes HSMA continues running still further, even though the stop criterion is achieved. In this way, the graphics show that convergence is often reached in the fewest iterations of the optimization process. The segmented images provide evidence that the outcome is better with threshold th = 2 and th = 3.

V. CONCLUSION

The multilevel thresholding (MT) method based on the harmony search algorithm (HSA) is proposed in this work. This work utilizes the good search capabilities with HSA and the use of some popular MT methods such as Otsu and Kapur. In order to measure the performance, the peak signal to - noise ratio (PSNR) and standard deviation (STD) is used to assess the segmentation quality by considering the coincidences between the segmented and the original images. Experimental results show that the Otsu delivers better results than the Kapur criterion. Although the results offer evidence to demonstrate that the standard HSA method can yield good results on color satellite images.

REFERENCES

[1] Agrawal. S , Pand. R., Bhuyan .S, Panigrahi .B. (2013). "Tsallis entropy based optimal multilevel thresholding using cuckoo search algorithm", Swarm and Evolutionary Computation, (11) , 16–30.

[2] Akay .B. (2013), "A study on particle swarm optimization and artificial bee colony algorithms for multilevel thresholding", Applied Soft Computing, 13(6), 3066–3091.

[3] Ashish Kumar Bhandari , Vineet Kumar Singh , Anil Kumar , Girish Kumar Singh . (2014) "Cuckoo search algorithm and wind driven optimization based study of satellite image segmentation for multilevel thresholding using Kapur's entropy", Elsevier Expert Systems with Applications (41), 3538–3560.

[4] Bhandari .A.K, Kumar .A, Singh .G.K.(2015)," Modified artificial bee colony based computationally efficient multilevel thresholding for satellite image segmentation using Kapur's, Otsu and Tsallis functions", Expert Systems with Applications (42) ,1573–1601.

[5] Bhandari .A.K , Kumar .A , Chaudhary .S , Singh .G.K.(2016), "A novel color image multilevel thresholding based segmentation using nature inspired optimization algorithms", Elsevier Expert Systems With Applications (63),112–133.

[6] Brajevic .I, Tuba .M. (2014), "Cuckoo search and firefly algorithm applied to multilevel image thresholding in Cuckoo search and firefly algorithm", (pp. 115–139).

[7] Geem, Zong Woo, Joong Hoon Kim, and G. V. Loganathan (2001). "A new heuristic optimization algorithm: harmony search." Simulation 76.2: pp. 60-68.

[8] Kapur .J. N, Sahoo P. K, & Wong A. K. C. (1985), "A new method for gray-level picture thresholding using the entropy of the histogram", Computer Vision Graphics Image Processing, 29, 273–285.

[9] Liu .Y, Mu .C, Kou .W, & Liu .J. (2014), "Modified particle swarm optimization-based multilevel thresholding for image segmentation", Soft Computing, 1–17.

[10] Manikandan.S,Ramar.K,Willjuice Iruthayarajan.M, Srinivasagan.K.G. (2014), "Multilevel thresholding for segmentation of medical brain images using real coded genetic algorithm", Measurement (47),558–568.

[11] Mala .C, & Sridevi .M. (2015), "Multilevel threshold selection for image segmentation using soft computing techniques", Soft Computing , 1–18 .

[12] Otsu N. (1979), "A threshold selection method from gray-level histograms", IEEE Transactions on Systems Man and Cybernetics SMC, 9(1), 62–66.

[13] Sparea .S, Kumar .A, Bajaj .V, Singh G.K.(2016), " A multilevel color image segmentation technique based on cuckoosearch algorithm and

energy curves", Elsevier Applied Soft Computing (47), 76–102.

[14] Rajinikantha .V, Couceiro .M.S. (2015), "RGB Histogram based Color Image Segmentation Using Firefly Algorithm", Computer Science (46) 1449 – 1457.

[15] Sanjay Agrawal, Rutuparna Panda, Sudipta Bhuyan, Panigrahi .B.K. (2013), "Tsallis entropy based optimal multilevel thresholding using cuckoo search algorithm", Evolutionary Computation(11)16–30

[16] Sathya .P, Kayalvizhi R. (2010), "PSO-based tsallis thresholding selection procedure for image segmentation", International Journal of Computer Applications, 5 (4), 39–46 .

[17] Sathya .P.D, Kayalvizhi .R.(2011), "Modified bacterial foraging algorithm based multilevel thresholding for image segmentation", Engineering Applications of Artificial Intelligence (24),595–615

[18] Shaoo P. K., Soltani .S, Wong .A. K. C., & Chen Y. C. (1988), "Survey: A survey of thresholding techniques", Computer Vision, Graphics, and Image Processing, 41,233–260.

[19] Shilpa Suresh, Shyam Lal . (2016), "An efficient cuckoo search algorithm based multilevel thresholding for segmentation of satellite images using different objective functions" ,Elsevier Expert Systems With Applications (58), 184–209 Contents lists.

[20] Soham Sarkar, Swagatam Das, Sheli Sinha Chaudhuri. (2016), "Hyper spectral image segmentation using Rényi entropy based multilevel thresholding aided with differential evolution" ,Expert Systems With Applications (50)120–129

[21] Tahir Saga, Mehmet unkas¸ (2015), "Color image segmentation based on multiobjective artificial bee colony optimization", Applied Soft Computing (34) 389–40.

[22] Tsai W. (1985), "Moment-preserving thresholding: A new approach", Computer Vision Graphics and Image Processing, 29, 377–393.

[23] Valentın Osuna Enciso , Erik Cuevas, Humberto Soss. (2013), "A comparison of nature inspired algorithms for multi-threshold image segmentation", Elsevier Expert Systems with Applications (40), 1213–1219.

[24] Yin .P.Y. (1999), "A fast scheme for multilevel thresholding using genetic algorithms", Signal Processing, 72, 85–95.

[25] Yin .P. Y. (2007), "Multilevel minimum cross entropy threshold selection based on particle swarm optimization",AppliedMathematicsand Computation, 184(2), 503–513.

[26] Zhang .Y, & Wu .L. (2011), "Optimal multi-level thresholding based on maximum Tsallis entropy via an artificial bee colony approach", Entropy, 13, 841–859.