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Image Segmentation using Different Optimization Technique

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Abstract:- In image segmentation field Multilevel thresholding is an important technique. However, in standard methods, the complexity of this method increases with the variation of number of thresholds value. To avoid this disadvantages, nature inspired meta-heuristic techniques are used. These meta-heuristic algorithms give near exact results in a reasonable time, which catches the attention of recent researchers for optimization. No matter what kind of optimization method , the solution set must be represented via some way. For example, GWO (Grey Wolf Optimizer) this method follows the grouping and hunting behavior of wolves, PSO (Particle Swarm Optimizer) inspired from foraging behavior of swarm of particles (assuming birds as particles). Above optimizer are applied on some standard images collected from USC SIPI, BSD 500 database. At end part, a comparison was made based on threshold values, image quality measures, and computational time .In this analysis, GWO based results and PSO based results are compared with the standard results .The results are compared in terms of thresholded images, image quality .Time complexity and plotting convergence plots, which shows the goodness of Grey Wolf Optimizer in terms of global search.

Keywords:- *Segmentation, thresholding, particle swarm, meta-heuristic, optimization.*

I. INTRODUCTION

Image is a method of transferring information and it holds lots of necessary information. Interpreting the image and collecting information from it to apply in some works is an important part of usefulness in digital image technology. Digital image processing is the utilization of different methods to do image processing on digital images[2]. And the very first step is the image segmentation. This is quite important phase and most challenging .Image segmentation partitions image into meaningful areas with homogeneous features and characteristics. Representing an image into an analyzable way is the aim of segmentation. The various uses of image segmentation are: Machine Vision, Bio metrics devices, Bio Medical Imaging, Face identification system, Fingerprint Recognition, vehicle Control Systems, Satellite Imagery, Video Surveillance etc. The success of image processing depends on accuracy of segmentation, but an accurate partitioning of an image is generally a very challenging problem.

II. MULTILEVEL THRESHOLDING

There are many techniques which are already utilized in segmenting the image. Different techniques have their individual significance. Histogram based thresholding technique is most popular and widely used because of its simplicity. Thresholding is one of the most popular and easiest technique and it can work with the noisy pictures.

A. Otsu's method of Multi- level thresholding

This is an extension to the Otsu et al. Let us consider an image with N number of pixels having gray value [1,2,3,…..,L] and let us assume there are "m" number of thresholds given as $t_1, t_2, t_3,\ldots, t_m$. Depending on these thresholds, there are m+1 number of classes[8]. Now, the class distributions are

$$C_1 = \frac{P_1}{W_1(t)},\ldots\frac{P_t}{W_1(t)} \qquad (1.1)$$

$$C_2 = \frac{P_1}{W_2(t)},\ldots\frac{P_t}{W_2(t)} \qquad (1.2)$$

$$C_{m+1} = \frac{P_1}{W_{m+1}(t)},\ldots\frac{P_t}{W_{m+1}(t)} \qquad (1.3)$$

Where

$$W_1(t) = \sum_{i=1}^{t} P_i \qquad (1.4)$$

$$W_2(t) = \sum_{i=t+1}^{t_2} P_i \qquad (1.5)$$

$$W_3(t) = \sum_{i=t_2+1}^{t_3} P_i \qquad (1.6)$$

$$W_{m+1}(t) = \sum_{i=t_m+1}^{L} P_i \qquad (1.7)$$

Let μ_T represent the average intensity of entire image, which is expressed as:

$$\mu_T = W_1\mu_1 + W_2\mu_2 + W_3\mu_3 + \ldots\ldots + W_{m+1}\mu_{m+1}$$

$$W_1 + W_2 + W_3 + \cdots\ldots + W_{m+1} = 1 \qquad (1.8)$$

According to Otsu et al, between class variances is expressed as

$$\sigma_B^2 = W_1(\mu_1-\mu_T)^2 + W_2(\mu_2-\mu_T)^2 + W_3(\mu_3-\mu_T)^2 + \ldots\ldots\ldots W_{m+1}(\mu_{m+1}-\mu_T)^2 \qquad (1.9)$$

In this case, threshold values have to be properly chosen to such that σ_B^2 will be maximized and that values of thresholds are the optimum thresholds[7].

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Classical derivative based optimum calculation is a time taking task for solving above equation for multilevel threshold, So recent researchers have focused on nature based meta-heuristic algorithm to find optimum thresholds.

III. METHODOLOGY

Gray wolf optimization methodology is a population based swarm intelligent method formulated by Mirjalli, Mohammod and Lewis (2014)[1]. This concept is developed from the group hunting of wolves and their social hierarchy.

A. Background knowledge

GWO follows the social grouping and the hunting techniques of wolves. They mostly stay in a pack and the size of the pack varies from 5 to 12.Then the entire pack is divided into four types of wolves named as Alpha (α), Beta (β), Delta (δ), and Omega (ω) in decreased order of their social hierarchy[3]. The dominant wolves are named Alpha. According to Munoz et al (2014), gray wolves hunting strategy involves three things

- Tracing
- Encircling
- Attacking

Mirjalili et al (2014) presents a mathematical ways of hunting behavior of wolves. The best solution is given by Alphas. The next two best analysis are given by Beta and Delta group respectively.

B. Encircling the prey

Gray wolves first enclose the prey to hunt. As mentioned in Mirjalili et al (2014),this nature is expressed as:

$$\vec{D}=|C.\vec{X}_p(t)-\vec{X}(t)| \quad (2.1)$$

$$\vec{X}(t+1) = \vec{X_p}(t) - A.\vec{D} \quad (2.2)$$

Where $\vec{D}$ =parameter to find new position of wolf
$\vec{X_p}$ = The position vector of the prey
$\vec{X}$ = The Gray wolf position
A & C are the coefficients

t = No of iteration

According to Mirjalili et al (2014)

$$A = 2ar_1 - a \quad (2.3)$$
$$C=2.r_2 \quad (2.4)$$

Where a = is a linearly decrease from 2 to 0
r_1 and r_2 = Two random values in [0,1]

C. *Hunting Behavior*

This behavior is modeled by Mirjalli et al. (2014) as

$$\vec{D}_\alpha = |C_1.\vec{X}_\alpha\ (t) - \vec{X}| \quad (2.5)$$
$$\vec{D}_\beta = |C_2.\vec{X}_\beta\ (t) - \vec{X}| \quad (2.6)$$
$$\vec{D}_\delta = |C_3.\vec{X}_\delta\ (t) - \vec{X}| \quad (2.7)$$
$$\vec{X}_1 = \vec{X}_\alpha - A_1 \quad (2.8)$$
$$\vec{X}_2 = \vec{X}_\beta - A_2 \quad (2.9)$$
$$\vec{X}_3 = \vec{X}_\delta - A_3 \quad (2.10)$$

Where $\vec{X}_\alpha$, $\vec{X}_\beta$, $\vec{X}_\delta$ are the position vector of α–wolves, β-wolves and δ-wolves respectively and $A_1, A_2, A_3, C_1, C_2, C_3$ are the coefficients.

The best position of wolf is defined as:

$$\vec{X} = (\vec{X}_1+\vec{X}_2+\vec{X}_3)/3 \quad (2.11)$$

D. *Exploitation*

Gray wolves stops hunting process by killing the prey. Value of the ‘a’ decreases from 2 to 1 and the value of ‘A’ randomly chosen [-2a, 2a]. When |A|< 1; wolves kill the prey.

E. Exploration

Gray wolves slowly moves apart from each other to explore the location of the prey. To model it mathematically ,”A” is utilized. When |A|>1 i.e. either greater than 1 or less than 1,which focuses on global searching, the gray wolf diverge from prey position to get an improved position in the search space. This technique uses another parameter “C”. This parameter support exploration behavior, by giving random weight to prey[4]. This parameter is quite useful to avoid local optimum.

F. Algorithm

Step 1: Initializing the population of the wolves and also the value of a, A, and C.

Step 2: Compute the objective values of the individual wolf and find the best three position of wolves as $\vec{X}_\alpha$, $\vec{X}_\beta$, $\vec{X}_\delta$

Step 3: Improve the position of the current wolf

Step 4: Estimate the individual fitness value of all wolves and update the value of $\vec{X}_\alpha$, $\vec{X}_\beta$ and $\vec{X}_\delta$

Step 5: Check for stopping criteria; if satisfied consider the best value of solution otherwise go to step 3

G. Image Thresholding

The most popular Otsu methodology is used to find out the threshold values. This Otsu method maximizes in between class variances to find optimum thresholds. As GWO minimizes the function, so according to Abdul et al.(2019) ,its minimization version is considered as objective function.

$$T' = \frac{1}{1+\sigma_B^2} \quad (3.1)$$

In this method, wolf are represented as search agent assigned with the initial threshold values and allowed to search for the best optimum thresholds by moving in search space of n-dimensions according to the number of thresholds[1].

IV. RESULT

The algorithm is implemented in Matlab 2016a with Intel core i3-CPU @2.30 GHz ,with 64 bit OS and 4GB RAM. For the methodology 12 numbers of wolves are considered and 500 iteration are done for getting best values and images are collected from BSD 500 and USC-SIPI databases.

figure	m	Threshold values(PSO)
Lenna	4	75,114,145,183
	5	67,96,123,150,183
Pepper	4	40,88,134,174
	5	43,79,112,145,177
Baboon	4	72,106,137,168
	5	69,101,126,150,176
Man	4	35,82,124,164
	5	30,67,102,136,173
Airplane	4	84,129,172,203
	5	70,107,144,181,206
Starfish	4	59,99,136,186
	5	54,84,112,149,192
Snake	4	70,102,130,169
	5	66,94,118,143,178
Zebra	4	85,113,143,200
	5	76,99124,152,205

Table 1: Threshold values(PSO)

figure	m	Threshold values(GWO)
Lenna	4	75,114,145,180
	5	74,110,137,161,189
Pepper	4	41,89,135,175
	5	42,79,114,148,179
Baboon	4	72,106,137,168
	5	68,99,125,150,176
Man	4	35,82,124,164
	5	29,66,101,135,172
Airplane	4	84,129,172,203
	5	70,108,144,181,206
Starfish	4	60,101,138,187
	5	53,87,118,151,195
Snake	4	70,102,130,167
	5	64,91,115,140,174
Zebra	4	84,112,142,194
	5	78,102,15,154,207

Table 2: Threshold values(GWO)

figure	m	Objective values	
		PSO	GWO
Lenna	4	2192.57	2192.50
	5	2217.04	2218.57
Pepper	4	3153.57	3153.45
	5	3197.43	3198.44
Baboon	4	1693.23	1694.16
	5	1719.92	1719.92
Man	4	3209.86	3209.86
	5	3255.84	3255.73
Airplane	4	2819.56	2815.87
	5	2097.09	2097.13
Starfish	4	2867.78	2870.42
	5	2916.73	2917.23
Snake	4	1286.51	1286.68
	5	1316.53	1316.58
Zebra	4	1590.89	1591.82
	5	1618.13	1619.24

Table 3: Objective values

figure	m	SSIM values	
		PSO	GWO
Lenna	4	0.7929	0.7962
	5	0.8194	0.8191
Pepper	4	0.7421	0.7428
	5	0.7763	0.7777
Baboon	4	0.8606	0.8666
	5	0.8921	0.8958
Man	4	0.6819	0.6909
	5	0.7351	0.7375
Airplane	4	0.8493	0.8521
	5	0.8759	0.8763
Starfish	4	0.7816	0.7816
	5	0.8250	0.8278
Snake	4	0.8783	0.8777
	5	0.9070	0.9085
Zebra	4	0.8493	0.8493
	5	0.8735	0.67

Table 4: SSIM values

figure	m	Computational time in seconds	
		PSO	GWO
Lenna	4	3.800	4.005
	5	4.060	4.279
Pepper	4	3.7049	3.7192
	5	4.006	3.992
Baboon	4	7.9602	7.9961
	5	8.195	8.220
Man	4	4.7462	4.7818
	5	5.016	4.993
Airplane	4	3.7876	3.8645
	5	4.077	4.178
Starfish	4	5.4080	5.4501
	5	5.757	5.672
Snake	4	5.4829	5.5225
	5	5.948	5.822
Zebra	4	5.2873	5.3149
	5	5.522	5.446

Table1.5 Computational time (sec)

Fig. 1: (PSO mm=5)

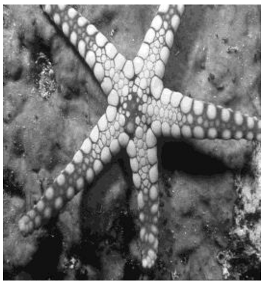

Fig. 2: (GWO m=5)

Fig. 3: (PSO m=5)

Fig. 4: (GWO m=5)

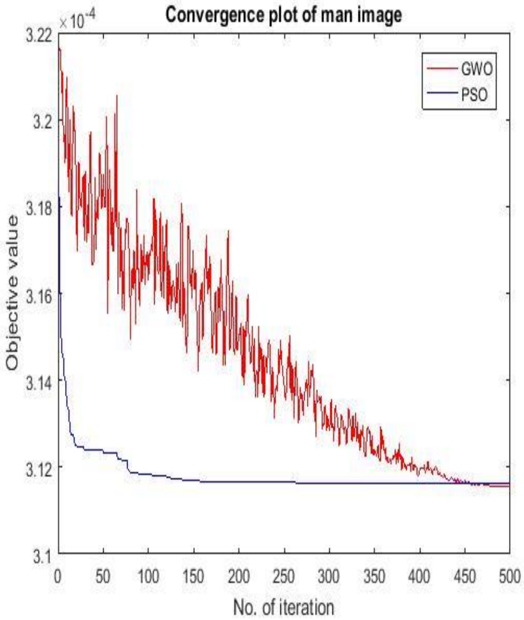

Fig. 5: Convergence plot of man image

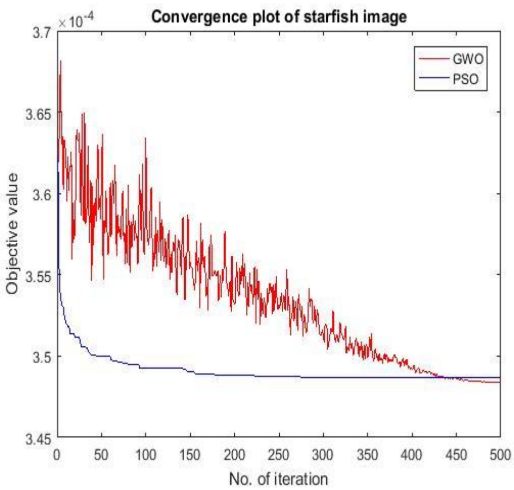

Fig. 6: Convergence plot of starfish image

V. CONCLUSION

Thresholding is the prime step in image analysis. Therefore, higher level image application depends on the thresholding results. The literature figures nature based methods are quite popular and applied to different fields. The probabilistic analysis of these methods touch close to optimum value in a reasonable time. In this work, particle swarm optimizer and grey wolf optimizer is implemented for finding optimum threshold in case of multilevel thresholding. Both the algorithm have its own advantage. To check the performance of methods, structural similarity value is taken to understand the segmentation quality. The performance of each approach is demonstrated in terms of similarity value and convergence plots. According to the statement 'No free Lunch' there no particular meta-heuristic optimization principle which will show best performance in all scenario. Each methodology has its own specialty. Here GWO shows better convergence and high image quality as compared to others.

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