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MULTI-LEVEL IMAGE THRESHOLDING USING IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

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***Abstract* — Image segmentation is a basic problem in computer vision and various image processing applications. In this paper, a minimum cross entropy (MCE) based multilevel thresholding is presented to find the desired content of an image of interest. Excellent result is obtained for bi-level thresholding and the exhaustive search for optimal threshold values for multilevel thresholding is reduced by objective function such as MCE based improved particle swarm optimization (IPSO) metaheuristic algorithm drifting the pointer towards the fine-tuning search. The searching ability of the algorithm is improved by including the chaotic sequences of inertia weight factors of classical particle swarm optimization (PSO). The performance of IPSO is analysed extremely through comparison with other well-known global optimisation techniques such as genetic algorithm (GA) and PSO. This proposed approach depicts its efficiency and effectiveness by testing on two military test images to provide high quality segmented images.**

***Index Terms*— Improved particle swarm optimization, military image, minimum cross entropy, multi-level thresholding.**

I. Introduction

Image segmentation is the basic operation in the field of image processing to segment the meaningful part of an image based on its shape, size, colour or texture [1]. Thresholding technique is most widely used segmentation method to predict the object of interest from its background. Thresholding finds its applications in Extraction of character from an image (or) to identify the defects of electronic components, to detect the tissue deformities causing abnormalities in brain region. Image with two classes can be split by bi-level thresholding whereas image with more than two classes will be partitioned by a simple, powerful, accurate and robust multilevel thresholding technique [2]. This method utilizes the intensities for object identification. Pixels with same values of intensities describe the desired object of one class by multilevel thresholding [3]. However, exponential increase in number of thresholds increases the computational time. MCE based global thresholding has received considerable attention to work on image segmentation. This problem is overcome by Minimum cross entropy based multilevel thresholding, capturing average information content of events defining the entropy [4].

Advancement in Information theory proposed various entropy models such as Shannon entropy, Renyi entropy, Tsalli's entropy and Cross entropy has been proposed for bilevel thresholding but, multilevel thresholding suffers from high computational cost resulting in exhaustive search for best T Threshold values. Nonconvexity and ruggedness reduces the convergence rate by MCE based multilevel thresholding. This MCE calculate the cost function depending on total entropy criteria and minimises it by global optimisation algorithms. This MCE minimises the cross entropy between the standard and obtained segmented image. In this work, multilevel thresholding technique is introduced based on MCE aided with IPSO algorithm.

High quality solutions for difficult problems are provided by widespread metaheuristic algorithms [5-7]. PSO is a simple, easy and computational efficient algorithm, when compared with other heuristic techniques. But PSO get struck in local optima. To overcome this drawback, IPSO aided with MCE is proposed in this paper. Global optimal point is reached by enhancing the ability of group interaction of particles through its ability to retain its past knowledge to return towards them when they deviate from the desired destination.

II. Objective Function of MCE

Minimum Cross entropy [8] provides factual knowledge about the specific path to reach the global point by finding the difference of true and predicted distribution.

Let theProbabilities of same set representedas P = $\{p_1, p_2 \ldots p_z\}$ and Q = $\{q_1, q_2 \ldots q_z\}$.

Information gain between the distances P and Q:

$$I(p,q) = \sum_{i=1}^{z} p_i \, ln \frac{p_i}{q_i} \qquad (1)$$

Let an image has G gray levels from {0,1, 2, (G-1)}. Here, 1,2… G corresponds to histogram intensity levels. S be the true image considered and thresholded image S_m is given as:

Cross entropies minimum objective function is stated as:

$$\min\{I(m)\} = I_0 + I_1 \qquad (2)$$

$$I_0 = -\sum_{j=0}^{m-1} jh(j) \, log \left(\frac{\sum_{j=0}^{m-1} jh(j)}{\sum_{j=0}^{m-1} h(j)} \right)$$

$$I_1 = -\sum_{j=m}^{G} jh(j) \, log \left(\frac{\sum_{j=m}^{G} jh(j)}{\sum_{j=m}^{G} h(j)} \right)$$

Complex image information is received by Multilevel thresholding and for determining m dimensional optimization, the objective function is considered as:

$$\min \{S(m_0+m_1+m_2+\ldots+m_n)\} = I_0+I_1+I_2+\ldots+I_n \quad (3)$$

where,

$$I_0 = -\sum_{j=0}^{m_1-1} jh(j)\log\left(\frac{\sum_{j=0}^{m_1-1} jh(j)}{\sum_{j=0}^{m_1-1} h(j)}\right)$$

$$I_1 = -\sum_{j=m}^{m_2-1} jh(j)\log\left(\frac{\sum_{j=m}^{m_2-1} jh(j)}{\sum_{j=m}^{m_2-1} h(j)}\right)$$

$$I_2 = -\sum_{j=m}^{m_2-1} jh(j)\log\left(\frac{\sum_{j=m}^{m_3-1} jh(j)}{\sum_{j=m}^{m_3-1} h(j)}\right)\ldots$$

and

$$I_n = -\sum_{j=m}^{G} jh(j)\log\left(\frac{\sum_{j=m}^{G} jh(j)}{\sum_{j=m}^{G} h(j)}\right)$$

Effective result is obtained for bi-level thresholding, but computational time increases with the increase in count of threshold. To overcome the above problem IPSO based MCE algorithm is implemented to reduce the convergence rate by reaching global point with its excellent separation step based on intelligent move towards the goal.

III. IPSO ALGORITHM

A. *Basic Concept of PSO Method*

The most widely used particle swarm optimization algorithm is introduced by James Kennedy and Russel C. Eberhart (1995). The Intelligent metaheuristic algorithm finds its enormous applications in Machine learning, Data mining and in Image processing. PSO enhances the group interaction to reach the global optimum quickly and the 'memory' retention of previous knowledge trap the particles to return towards them [9 - 11].

In PSO, Particles move in D-dimensional space. Each particle '*i*' has a position $p_i = [p_{i,1}, p_{i,2\ldots} p_{i,D}]$ and a velocity $v_i = [v_{i,1}, v_{i,2} \ldots v_{i,D}]$.

In this, each particle keeps track of its co-ordinates in hyperspace to retain its fitness. The value of fitness stored is called '*pbest*', Stored overall best value and its location are called '*gbest* 'and each particle keeps track of neighborhood called ' *lbest*'.

The Standard PSO is described as:

$$V_{i,d}^{k+} = W \times V_{i,d}^{k} + C_1 rand_1 \times (pbest_{i,d}^{k} - X_{i,d}^{k}) + C_2 \times rand_2 (gbest_d^k - X_{i,d}^k) \quad (3)$$

$$X_{i,d}^{k+1} = X_{i,d}^{k} + V_{i,d}^{k+1} \quad (4)$$

$$i = 1,2\ldots\ldots, n;\ d$$

where W is a weighting factor; C_1 is the acceleration factor; $C_2$is a social acceleration factor; rand1 and rand2 are the random numbers between 0 and 1.$V_{i,d}^k$ is the velocity of particle i at iteration k; $X_{i,d}^k$is the dth dimension position of I at iteration k;pbest and gbest are the dth dimension of own best and best particle at iteration k.

Time varying weighting function W is given by:

$$W = W_{max} - (W_{max} - W_{min}) \times Iter/Iter_{max} \quad (5)$$

where W_{max} and W_{min} are initial and final weight respectively, Iter is the current iteration number and $Iter_{max}$ is the maximum iteration number.

B. *IPSO*

Chaotic behavior is depicted by equation:

$$f_k = \mu . f_{k-1} . (1 - f_{k-1}) \quad (6)$$

Where μ is a control parameter with the range between [0,4].

Variation of μmakes an intense variation in behavior of the system. The above equation displays chaotic dynamics with μ =4 and $f_0 \notin \{0, 0.25, 0.50, 0.75, 1.0\}$.

Here, global searching ability is improved by new weight :

$$W_{new} = W \times f \quad (7)$$

Weight parameter applied for chaotic sequences drives to reach the global optimal solution faster decreasing the computation time than PSO algorithm [12].

Step 1: The threshold value is taken as input.

Step 2: $W_{max}, W_{min}, C_1, C_2$ *and* $Iter_{max}$ parameters are initialized.

Step 3: Initialize random positions and velocities for N particles

Step 4: Fitness value is calculated using the objective function (1) or (2)

Step 5: *pbest* value is updated by comparing fitness value with *pbest* and if the current value is better than *pbest*, then the current value is set as *pbest*.

Step 6: *gbest* value is updated by comparing fitness value with *gbest* and if the current value is better than *gbest*, then the current value is set as *gbest*.

Step 7: Chaotic weight W_{new}^{k+1} is updated

Step 8: Calculate the velocities V^{k+1} using equation (3)

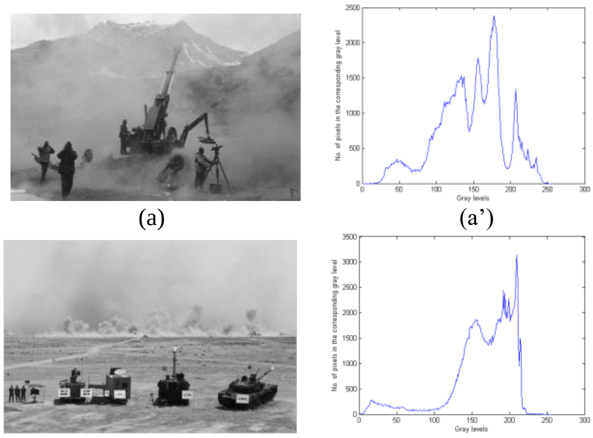
Step 9: Calculate the velocities X^{k+1} using equation (4)

Step 10: Step 4 is continued until the current iteration reaches the maximum iteration number

Step 11: Last iteration output's the optimal solution

IV. PERFORMANCE EVALUATION

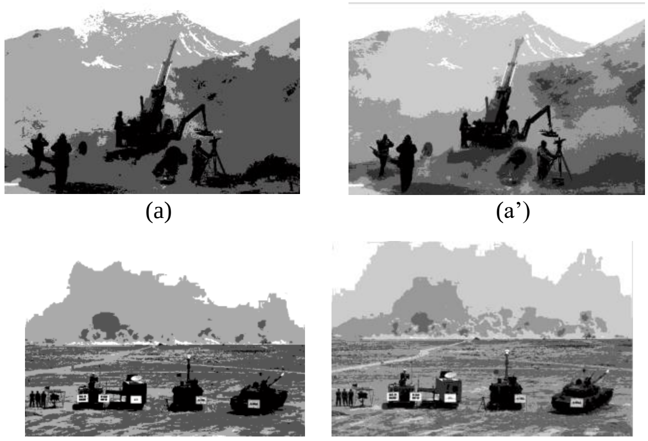
The proposed IPSO with MCE based thresholding technique is tested on the military images. The images and their histograms are given in Figure 1. The comparative studies with GA, PSO algorithms serve to justify the performance of the proposed IPSO algorithm.



(a) (a')

(b) (b')

Fig.1. Military images with their histograms
(a) Military image1 (b) Military image 2



(a) (a’)

(b) (b’)

Fig. 2. Segmented military images obtained by MCE-IPSO algorithm
[(a), (a’) are the thresholded images when m = 3,
(b), (b’) are the thresholded images when m = 5]

Table 1 Objective values

Test Images	m	Objective values (×10^9)		
		GA	PSO	IPSO
Military image 1	2	8.0354	8.0354	8.0254
	3	7.1073	6.8477	6.2590
	4	5.7179	5.3293	5.1563
	5	4.8328	4.6560	4.4930
Military image 2	2	8.0690	8.0690	8.0090
	3	7.2246	7.0479	6.6372
	4	6.3102	6.1902	5.8690
	5	5.0575	4.7100	4.2273

Table 2 Optimal threshold values

Test images	m	Optimal threshold values		
		GA	PSO	IPSO
Military image 1	2	127,181	127,181	127,181
	3	84,132,198	71,134,188	90,151,190
	4	58,101,154, 196	78,106,149, 186	64,119,157, 188
	5	44,84,131,172, 206	54,94,135, 164, 206	66,105,132,160, 190
Military image 2	2	140,190	140,190	140,190
	3	87,140,190	93,160,188	100,154,190
	4	71,106,152, 193	59,106,157, 198	45,120,165,200
	5	80,111,161, 191,203	76,113,134, 159, 200	68,106,136,184, 218

The objective values and the corresponding optimal threshold values obtained through IPSO algorithm are compared with that of the aforementioned algorithms in Tables 1 and 2 respectively. It is clear from the comparison that the IPSO algorithm generates better solutions than the GA and PSO algorithms.

The segmented military images with three and five thresholds are shown in Fig. 2. It can be seen from the Fig. 2 that the segmentation quality is better with five level thresholding.

V. CONCLUSION

In this paper an optimal multilevel thresholding using MCE based IPSO algorithm has been described. The performance of the proposed algorithm has been compared with conventional PSO and GA methods by considering two military images as test images. The experimental results show that the proposed scheme can accelerate the optimal thresholding methods in the multilevel thresholding case and the quality of the thresholded images is better that those of property-based multilevel thresholding methods such as GA and PSO algorithms. The experimentally evaluated results show that the proposed IPSO based MCE approach for multilevel image segmentation can accurately and efficiently examine for multiple thresholds, which are near to optimal ones searched using an exhaustive search process.

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