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A Multi-level Thresholding for Image Segmentation using Improved PSO Algorithms

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Abstract: Image is a collection of pixel or voxel which is used to manipulate and analyze the consisting data in digital format. Processing of an image is done to improve the quality and magnify the required data. In the proposed method, threshold based image segmentation is used in which multi-level thresholding is done to carry out multiple thresholds values of a single image which is performed by maximizing the objective function. Here different variants of PSO i.e., Particle swarm optimization (PSO), Darwinian PSO (DPSO), Fractional-order Darwinian particle swarm optimization (FO-DPSO) is used on gray scale images to improve the quality, CPU time and find the optimal threshold value.

Keywords: *Image segmentation, PSO, DPSO, FO-DPSO, multi-level thresholding*

I. Introduction

Image segmentation is a process of segmenting an image based on pixels and non-intersecting regions. Segmentation is classified in 4 types in which one of the methods is threshold based segmentation. Threshold based segmentation is one of the best segmenting method for image segmentation. Threshold values calculate the object pixels and background pixels of an image which is distinguished by their gray scale values. In multiple thresholding method an optimal threshold value can be chosen to find the adequate object and segmented image from the gray scale image.

In the proposed method, one of the nature inspired algorithm is used i.e., PSO. Particle swarm optimization is a metaheuristic approach based on swarm behavior e.g. flock of fish, which helps to find the best region from the image as it contains a fixed size population over the search space randomly. Here, different variants of PSO are used on the gray scale image to get the required threshold value and CPU time.

PSO Algorithm:

T=0
Initialize population P(t)
While do
Begin
Evaluate each particle in P (t)
Update each particles global and local best positions
Update each particles position and velocity in P (t)
END

Darwinian Particle swarm Optimization (DPSO):

The problem of local optima among the optimization problems is resolved by Darwinian. In this a natural selection based search for local optimum is utilized when the previous search area is discarded and another area is searched for the resultant image.

Steps of DPSO

- Each swarm individually performs just like an ordinary PSO algorithm where the natural selection is done with the collection of swarms.
- The random selection of the swarms between a region constantly changes.
- Once the current local optimum expires, an update goes to the global optima to restart the algorithm and the new random selection starts based on fitness particles.

Fractional Order-Darwinian Particle swarm optimization (FO-DPSO)

The FO-DPSO is an improved version of DPSO where the maximum and minimum number of particles of a swarm is taken from the desired population size.

Table 1: Different categories of nature inspired algo With different parameters and benefits

Name	Methodology	Parameter	Application	Benefits
Bacterial Foraging	This is an evolutionary process based foraging bacteria in which poor foraging strategies are eliminated and successful foraging strategies are propagated for swarming and reproduction of genes.	1. No. of bacterium. 2. No. of chemotactic steps. 3. No. of reproduction steps. 4. Swimming length. 5. No. of elimination of dispersal events.	1. Object recognition. 2. Segregation of rotten fruits. 3. Brain MRI image.	1. Efficient Computational time. 2. Lowest standard deviation. 3. Converges quickly.
Differential Evolution Approach	This approach is based on differentiation for maximizing the computational equation for the randomly initialized search of the population.	1. No. of posteriori class probabilities. 2. Fitness evaluation. 3.Vector.	1. Graphical images. 2. Digital media. 3. Tissue images.	Robustness in optimization technique.
Genetic Algorithm	The fitness function solution, crossover & mutation managed to get near to the desired optimal solution. The mutation value should not be less than 0.5	1. Population size. 2. Cross over probability. 3. Mutation probability. 4. Encoding	1. Medical images. 2. Pattern recognition.	1. Computational speed. 2. Improved CPU time.
Multi Objective Genetic Algorithm(MOGA)	MOGA is multi-objective values for mutation and crossover.	1. Mutation probability. 2. Encoding. 3. Population size. 4. Cross over probability.	1. Biometric 2. Face expression detection. 3. Image restoration	Accuracy
Particle swarm optimization.	The PSO is a parallel computation technique which randomly picked population of initialize swarm.	1. Swarm size. 2. Inertia weight. 3. Learning factor.	1. Optimum contrast enhancement. 2. Natural image. 3. Human face image.	1. Good convergence speed. 2. Stable. 3. High segmentation speed.
Ant Colony Optimization.	The concentration of Pheromene on the way tolls the quality of food source at the end of the path.	1. No. of Generations. 2. Population size. 3. Priori constraint. 4. Persistence of trials.	1. Data retrieval. 2. Fingerprint recognition system.. 3. Control based image retrieval 4. Pattern matching. .	1. Consistent image quality. 2. High classification accuracy. 3. Optimal solution.
Bee Colony Optimization.	The leader shows the best place to form their bee hive so that each food source is identified.	1.No. of food source. 2. No. of neighbors. 3. Colony size.	1. Noisy image quality evolution. 2. Random images. 3. Image recognition.	1. Less computational speed. 2. Efficiency.
Simulated Annealing	Simulated Annealing will work same as process of annealing in metal work	1. Temperature variable 2. No. of process.	Smoothness	Finite optimal solution.
Artificial Bee Colony Algorithm	The employed bees are assigned to their food sources and the amount of nectar is by the onlooker bees.	1. No. of food sources. 2. Limit	1. Wireless Sensor Network 2. Medical Imaging	1. Faster Convergence Speed 2. High Performance
Cuckoo Search	Every single cuckoo lays one egg at a time, and dumps it into a randomly chosen nest with best nest quality of eggs.	1. No. of cuckoo’s 2. No. of availability of Host nest 3. best nest	Satellite Images	1. Image Contrast 2. Brightness enhancement
Firefly Algorithm	It Works with Gaussian distribution function and applied to optimize the load for water chiller air conditioning systems	1. No. of iterations. 2. No. of threshold values. 3. Gray scale images. 4. Mutation ratios. 5. Mutation value.	1. Pattern recognition. 2. Image comparison.	To solve complex problem of image processing.
Spider Monkey Optimization(SMO)	SMO is swarm intelligence based approach which is inspired by intelligent foraging behavior of fission- fusion social structure based animals.	1. Swarm size. 2. Global leader limit. 3. Local leader limit. 4. Threshold value.	1. Medical image processing. 2. Cell images. 3. Antennae optimization.	1. Less CPU time. 2. Less iteration than PSO.
Social Spider Colony optimization(SSCO)	Social insect societies are complex cooperative systems that self-organize within a set of constraints.	1. No. of communal web. 2. Mating operator. 3. Vibration modeling.	1. Numerical optimization. 2. Multi Thresholding	1. Adaptation 2. Modularity. 3. Fault tolerance. 4. Parallelism.

FO-DPSO improves the ability of PSO algorithm, by demolishing the local optimum problem while running the parallel PSO simultaneously with several swarm particles among the same population size.

FO-DPSO is an stochastic approach and depends on uniformly distributed variables. Hence, it is most commonly used for global optimum of an problem without affecting the local optimum.

II. Problem statement

To implement an effective Nature Inspired algorithm for Multi-level Thresholding for image segmentation based on an appropriate objective function. The optimal thresholding methods search the thresholds such that the segmented classes on the histogram satisfy the desired property. This is performed by maximizing an objective function which uses the selected thresholds as the parameters.

Goal

To develop an algorithm for multi-level thresholding in terms of speed and optimal convergence, this can be considered for a wide variety of problems in image segmentation.Some optimization methods are fast but not efficient (for finding the global optimum) and vice versa.This significantly improves the accuracy by optimizing and finding the optimal threshold values for the segmented image

Scope

Applying the FODPSO to the segmentation of images may allow achieving both vital important goals at once. More specifically, due to its convergence speed, this optimization method may present itself as a potential solution to a wide variety of complex problems like image analysis etc.

III. Implementation and Testing

Step 1: The image is split into gray scale matrix values.**Step 2**: PSO, DPSO and FODPSO is applied on the input image to get the desired segmented image. The values of the segmented image and thresholding values will be compared.**Step 3:** With the help of these values the histogram of the segmented image will be formed.**Step 4**: Then it will give the intensity values of the image and convergence time for each of the used algorithms along with the segmented image and histograms, which will be the final result

Proposed Architecture

The proposed algorithm is devoted with Otsu's and Kapur's objective function and compared with the DPSO and FODPSO algorithms. In this proposed work the gray scale image or microscopic image will be taken as input and it is preprocessed. During preprocessing the signal to noise ratio is reduced.

Then Otsu's and Kapur's function is maximized to get the desired threshold values. The obtained threshold value is used to get the histogram of the images which results in segmented image. The resultant segmented image are tested on the standard test images. This process is iterated until the optimum threshold value is gained and satisfies the benchmarked functions

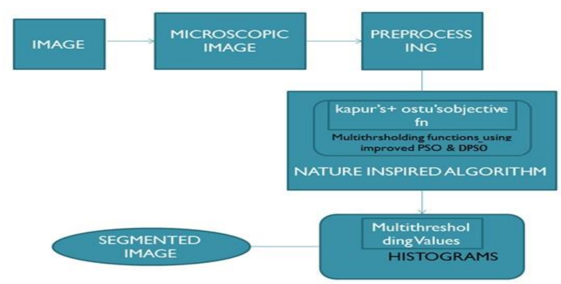


Fig1. Proposed Architecture

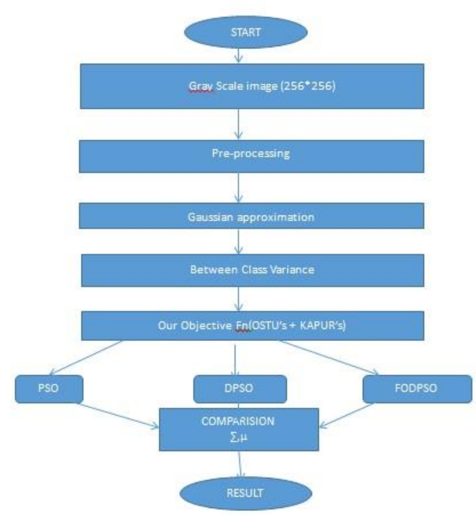


Fig2.Workflow of the system

The workflow of the system describes that the image .jpg format is taken as input and is preprocessed, while preprocessing the noise is reduced and the pixel values are obtained in the matrix form. After this the Gaussian approximation will also check for further noise reduction and will remove the noise, the pixels which are not efficient or crashed and gives the matrix values for which the segmentation is to be processed.

Otsu's between class variance is taken as an objective function which will maximize the variance and fix the fitness value for the required algorithms to perform the analysis. During this process we will get the intensity values of the image which will be processed with the algorithms mentioned above to perform the segmentation.

Input images

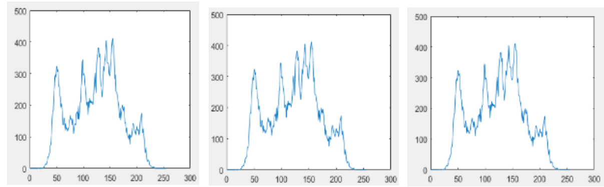
(a) Lenna image (b) Butterfly image

(c) Cameraman image (d) Cloud image

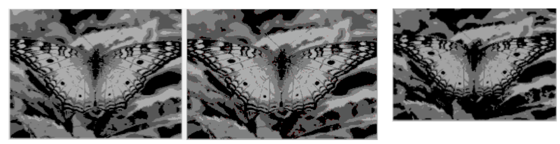
(e) Dog image (f) Baby image

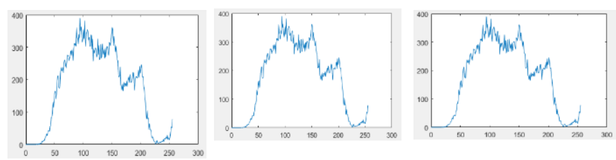
Segmented Images and Histograms

i.PSOii.DPSOiii.FODPSO



i.PSOii.DPSOiii.FODPSO





IV. Performance Analysis

Table 2: Analysis of the standard test images based on the original size and segmented size

Result Analysis		Image1 Lenna	Image2 butterfly	Image3 camera	Image 4 Cloud	Image 5 Dog	Image 6 Baby
Original Size (.jpg) in KB		14.5	17.7	14.4	12.8	14.1	5.10
Segmented Size in KB (.fig)	PSO	37.0	66.9	34.2	32.6	63.7	37.2
	DPSO	37.4	67.8	34.0	32.8	63.8	37.1
	FODPSO	37.6	68.2	34.3	32.9	64.9	36.9
Execution Time (in seconds) when m=3,4 using FODPSO		20.013 18.109	51.874 67.398	13.049 11.422	23.26 22.74	27.570 24.115	26.617 24.191

The gray scale image taken as an input with the original size mention in the above table will be processed based on the objective function between class variance criterion and after that the image is segmented on the algorithms which help us to get the required segmented image. As all can see that after the segmentation process is over the size of the image is increased.

The CPU time and Fitness Value of the processing image has been listed below in the table.

Table 3: The CPU time of processing an image

Image	Fitness Value	CPU Time in seconds with thresholds m = 3,4		
		PSO	DPSO	FOPSO
lenna	1.5677e03	4.1842,3.9523	3.9369,3.7067	3.7693,3.4863
butterfly	1.5527e03	4.0235,4.1348	4.0377,4.0947	4.0347,4.0831
cameraman	3.1794e03	4.0344,4.0241	4.0120,3.9782	4.0112,3.9478
Cloud	2.5007e03	4.2536,4.2368	4.1998,4.0971	4.0642,3.8088
Dog	2.3706e03	4.1204,4.2374	4.1102,4.0722	4.0625,3.9971
Baby	2.3338e03	4.1250,4.1505	4.0648,4.1056	4.0684,4.0345

Table 4: Optimal Threshold values of the input image

Image	No. of Thresholds	Threshold Values		
		PSO	DPSO	FODPSO
lenna	3	150,92	151,93	151,93
	4	169,124,79	169,124,79	170,125,80
Butterfly	3	162,106	183,107	163,107
	4	172,127,86	173,128,87	172,127,86
cameraman	3	145,71	146,72	146,72
	4	202,142,72	202,142,70	203,143,71
Vegetables	3	154,81	155,82	155,82
	4	173,116,69	174,117,70	173,116,69
Cloud	3	161,93	162,94	162,94
	4	188,143,89	189,144,90	188,143,89
Plane	3	117,67	118,68	117,68
	4	128,107,61	129,108,62	128,108,62
Ostrich	3	136,74	137,75	137,75
	4	152,101,68	152,101,68	152,101,68
Dog	3	197,131	198,132	197,131
	4	202,142,89	202,142,89	202,142,89
Baby	3	173,100	174,101	174,101
	4	190,145,87	191,146,88	190,145,87

V. Conclusion

In this Paper, a swarm intelligence based meta-heuristics techniques using multi-objective approach has been proposed, which facilitates determining predefined number of threshold values of test images for multi-level thresholding environment based on PSO, DPSO and FODPSO optimization algorithm.

The following features can be demonstrated supporting the proposed techniques:

1. Is computationally efficient and convergence speed is high as compare to other classical approaches.
2. Identifies computational complexity grows linearly with the number of thresholds.
3. CPU time is enhanced as compared to classical PSO and its variants.

Future research is needed, however to clarify the effect of randomness, the swarm topology with the function being minimized. If we can set the iterative parameters to some very small constant values then it may give a better segmentation and can also be used for Medical Imaging.

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