Cumulative Histogram based Dynamic Particle Swarm Optimization Algorithm for Image Segmentation

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Abstract - Image Segmentation is an essential part of image processing to recognize an image. It is the process to find the subsets of an image on the basis of its characteristics such that values or/and position of pixels. The computational complexity of these type of problems are considered as an NP-complete problem, it is a very hard task to find the solution to such types of problems. A heuristic algorithm like GA, ACO and PSO can be used to find the solution of such type of problems. In the proposed approach the Dynamic Particle Swarm Optimization (DPSO) was used to find the approximate solutions for Image segmentation. Cumulative Histogram will be used to find initial random populations of the Swarm. The result found from this algorithm is tested at different levels of measurement and compare with existing PSO algorithm

Keywords: Image Segmentation; Cumulative Histogram; Approximate Solutions; Multilevel Thresholding; Particle Swarm Optimization.

1. Introduction

Image segmentation is an important step in Image processing. Image segmentation discriminates the image on the basis of color, intensity, texture etc [2]. Image segmentation helps to analysis the image and extracts meaningful data from the image. Image segmentation has different techniques to segment an image like Thresholding technique, Edge detection technique, Region-based technique and Cluster-based technique etc. There are also some soft computing approaches to segment an image, those are Particle Swarm Optimization, Fuzzy based approach, Neural Network approach, Genetic Algorithm and Differential Equation. Soft computing approaches give approximation result or solution to complex problems that could not be solved in polynomial time.

Thresholding is an easiest and stable traditional approach of image segmentation, so it has become one of the most popular methods at the present time [3]. Thresholding also categorized into different techniques such as Histogram technique, Edge Maximization, Mean technique, Multilevel technique, P-tile technique etc [2]. The histogram is an effective thresholding technique of image segmentation. The histogram is based on the success of the calculation the thresholding value that discriminates the background from the object. It is difficult to determine the exact threshold value to separate an image into desirable objects from the background [4]. The histogram is a multilevel modal that divides the image into multiple parts that are objects and background so that image can be analyzed easily. These conventional techniques can be merged with soft computing approach so that one can find the optimal solution to the complex problems and make the computational process easy and fast.

PSO is the meta-heuristic technique that performs well and provides an optimal solution in less time complexity. In 2000 Omran introduced an improved PSO by modified its fitness function [5]. In 2003 Merwe introduced an image segmentation algorithm with the help of PSO. In this algorithm individual of the swarm are seeded by the result of the K-means algorithm [6]. In 2005 Omran [7] proposed a new algorithm DCPSO (Dynamic Cluster Particle Swarm Optimization). In this algorithm datasets are partitioning into clusters and that clusters are defined dynamically with the help of Particle Swarm Optimization [7]. Feng et.al. proposed a new method of image segmentation using 2-D maximum entropy with the help of the PSO method. In this approach threshold value can be found by 2-D histogram method [8]. Lin in 2007 proposed a PSO based algorithm for choosing multiple

minimum cross-entropy thresholds (MCET). The aim of this paper was to generate a recursive programming technique to reduce the computation complexity of the MCET [9]. Maitra in 2008 proposed an optimal multilevel thresholding algorithm with the help of improved variant of PSO. The hybrid approach uses both cooperative learning and comprehensive learning [10]. In 2009 Puranik introduced a new algorithm CLPSO. The aim of this algorithm was to develop a fuzzy system for image segmentation as well as color classification with a minimum error rate and less number of the rule. Velocity can be updated by the learning method [1]. In 2010 Sathya proposed a simple and histogram-based method for multilevel segmentation of an image. The proposed method combines the Tsallis Objective Function and PSO. It is used to find the threshold value for image segmentation [11]. In 2012 Mohsen introduced an algorithm which is a combination of PSO and Seed Region Growing (SRG). As we know seed initialization is a big problem so this algorithm overcomes the drawback of SRG by combining PSO algorithm. Each seed point contains its location and similarity difference, and this similarity difference and location refine by the PSO [12]. Lee also introduced a saliency directed color image segmentation using modified particle swarm optimization [13]. Liu in 2014 proposed a modified PSO algorithm (MPSO) based on multilevel thresholding to overcome the weakness of computational expenditure in conventional thresholding [14]. Mandal in 2014 proposed an algorithm for medical image segmentation using PSO aided level set based global fitting energy active contour approach [15].

PSO plays a crucial role in finding the best solution for a specified problem with efficiency with a higher probability of finding global minima. It may converge fast with minimum overlapping. Even these advantages there is some drawback also, PSO can be difficult to define inertia weight and initial design parameters. Inertia weight is inherited by the particle velocity and it determines the search capability of the particles. If Inertia weight and learning factors are not suitable then the algorithm may converge into local optima. Hence the result is forcibly converging to local minima. So to overcome this drawback Li in 2015 introduced a Dynamic PSO and K-means clustering (DPSOK) for segmentation of the image. In this paper inertia weight and learning factor also dynamically updated so that PSO does not fall into local minima [16]. Dhanachandra in 2020 also proposed an image segmentation approach based on fuzzy c-means and dynamic particle swarm optimization for better segmentation result [17].

This study proposes a dynamic approach of PSO with cumulative histogram. The study in this paper is arranged in five sections: Section two describes the related work about PSO and Cumulative histogram. Section three describes the proposed algorithm and section four discusses the result of the CHDPSO (proposed) algorithm. The last section concludes the study.

2. Related work

2.1. Particle Swarm Optimization

PSO is an evolutionary computational paradigm that came into existence in 1995 by Dr. Kennedy and Dr. Eberhart [18]. It is an evolutionary global search method that can efficiently compute complex problems [19]. The PSO was used to optimize the problem related to image reconstruction from small number of projections [22]. It is the population based optimization technique formed after the simulation of social and cooperative behavior of some species which try to find out their foods. They move in a group and cooperate. Optimization problems can be solved using it [17]. In PSO, a swarm of particles called particle flies through space. Each particle has some spatial position, velocity and fitness value, which are updated with the help of some optimization function. Each particle moves towards the best solution, each time it learns from its and other particles experience. During the movement, each particle preserves its best position which is based on a fitness function. This best position of a particle is called the personal best (Pbest) position. The best among all personal best positions of the particle is called the Global best (Gbest) position. Velocity and position of a particle updated with the movement of the particle (each individual in a particle). The factors which change velocity/position are current velocity, current position, Pbest position, Gbest position.

Let n is total number of particles of the swarm. The position of each individual in a particle is represented by X_i^P for iteration I and particle P . Fitness of particle P are

$$F_i^P = \text{fitness function}(X_i^P) \quad (1)$$

Personal best value of each individual in a particle P for iteration i can be calculated based on fitness value such that

$$F_{i^{Pbest}}^P = \text{minimum}(F_1^P, F_2^P, \dots, F_i^P) \quad (2)$$

Here i^{Pbest} is the iteration number for the personal or previous best fitness value of particle. Hence the personal or previously best position of particle $P = X_{i^{Pbest}}^P$ and the global best position of a particle is

$$Gbest = F_{i^{Pbest}}^{P^{Gbest}} = \text{minimum}(F_{i^{Pbest}}^1, F_{i^{Pbest}}^2, \dots, F_{i^{Pbest}}^n) \quad (3)$$

Where P^{Gbest} is the global best position of particle P .

Updated velocity is calculated as:

$$V_{i+1}^P = wV_i^P + c1r1 |X_i^P - X_{iPbest}^P| + c2r2 |X_i^P - X_i^{Gbest}| \quad (4)$$

Updated position calculated as:

$$X_{i+1}^P = X_i^P + V_{i+1}^P \quad (5)$$

For dynamic PSO, value of w will be changing dynamically

Figure 1. Flowchart of basic algorithm of PSO

2.2 Cumulative Histogram

The histogram represents the frequencies of the value of a variable interleaved (bin/bucket) into ranges that are, divide the whole range of values into intervals and then count how many values fall into each interval. It was invented by Karl Pearson [20]. It is like a bar chart except it groups the values into continuous ranges. These intervals described consecutive and intervals without overlapping of the variables.

Image Histogram: It is a type of histogram in which the x-axis and y-axis represented the gray values and frequency of a particular gray level of a pixel in an image. Histograms can be grouped into unimodal, bi-modal, and multimodal [21].

Let N be the number of pixels in an input image that is distributed in K number of gray levels.

$$N = \sum_{i=0}^{K-1} Xi \quad (6)$$

Where X_i is i^{th} gray level of a pixel in an image.

Normalized Histogram: a histogram can be normalized by adding probability density function in a normalized histogram the sum of all probability density value will be 1. A normalized histogram

$$Y_i = \frac{Xi}{N} \quad (7)$$

Cumulative Histogram: a cumulative histogram is like a graph between x-axis and y-axis in which $f(x)$ value is taken as a cumulative sum of $f(x)$ value. Cumulative histogram value can be calculated as:

$$Y_i = \sum_{j=0}^{j=i} \frac{X_j}{N} \quad (8)$$

3. Proposed Cumulative Histogram Dynamic PSO for Image Segmentation

Let X is an image of N number of pixels where $N = I \times J$ then $X(i, j)$ will be the gray value of the pixel. The proposed PSO algorithm for image segmentation has the following steps:

3.1 Particle Coding:

Each particle of the swarm will be coded by element of matrix P of size $(i \times j)$. If $p \in P$ is an element of matrix P then range of p will be integer value $\{0, 1, 2, \dots, K-1\}$ for K number of segmentation for image X .

Here each value of p will represent segments of image.

3.2 Initial value of population, velocity, inertia weight, learning factor of PSO algorithm:

The particle swarm optimization algorithm will be initialized by finding the threshold value with the help of cumulative histogram. Randomization of population will be done by selecting the random value closed to the segment boundaries.

Value of inertia weight w , learning factor $c1$ and $c2$ are initialized. Initial random value of velocity is also set.

3.3 Fitness Function

The optimization function can be used to calculate the Fitness function. The fitness function will describe the goodness of individual particle to find an approximate solution. CHDPSO (proposed method) fitness will be formulated as:

$$f_t = \frac{\sum_k^N \sum_i^N |x_{i,k} - C_k|}{\sum_k^N C_k} \quad (9)$$

Where C_k is the centroid of k^{th} segment and

$$C_k = \frac{\sum_i^N x_{i,k}}{N_k} \quad (10)$$

Where N_k will be the k^{th} segment's total pixels and $x_{i,k}$ will be the intensity value of k^{th} segment's of i^{th} pixel.

3.4 Dynamic weight:

The performance of an algorithm can be improved by adjustment of the inertia weight dynamically. As discussed above in the literature survey that fixed inertia weight may trap the algorithm into local minima problem and linearly decreasing in inertia weight, the algorithm loses the optimal solution. So to overcome this drawback of inertia weight in PSO makes the value of w dynamically. Its value will be change with iteration such as:

$$w = i / \text{no_of_iteration} \quad (11)$$

3.5 Updation of Velocity:

Let $V(i, j)$ be the velocity of the pixel (i, j) then updated new velocity will be calculated as

$$V = wV + c1r1|P - Pbest| + c2r2|P - Gbest| \quad (12)$$

Where $c1, r1, c2, r2$ are learning factors and w is the inertia weight.

3.6 Updation of position:

Position of particle will be updated by:

$$X(\text{new}) = X(\text{old}) + V \quad (13)$$

3.7 Termination Criteria:

The proposed algorithm will be repeated until a termination criterion is met, which is best on the number of iteration or fitness value.

Algorithm for proposed method (CHDPSO)

Step1: Initialization of random swarm population using cumulative histogram,

Initialization of random velocity for each swarm particle, inertia weight(w) and learning factors $c1$ and $c2$.

Step2: Repeat steps 3 to 6 until termination a criterion does not meet.

Step3: Find the value of fitness function for each Particle by equation (9).

Step4: Find the value of Personal best($Pbest$) and Global best($Gbest$) for each particle using equations (2) and (3) respectively.

Step5: update the dynamic inertia weight by equation (11).

Step6: Updation of Velocity of each Particle by equation (12).

Step7: Updating Position of each Particle by equation (13).

Step8: Check the termination condition.

Step9: End of the algorithm.

4. Result and Discussions

CHDPSO (proposed dynamic particle swarm optimization algorithm) is tested with a variety of gray colored images to find the segmentation result. These images are taken from mnist dataset and tested for different levels of segmentation. To check the performance with efficiency and convergence of chdpso method we select “dog” “jet plane”, “lena”, “peppers”, “walkbridge” as standard test gray images. The population is initialized with 10 particles and tested with 100 iterations. CHDPSO (proposed dynamic particle swarm optimization algorithm) is tested with a variety of gray colored images to find the segmentation result. These images are taken from mnist dataset and tested for different levels of segmentation. To check the performance with efficiency and convergence of chdpso method we select “dog” “jet plane”, “lena”, “peppers”, “walkbridge” as standard test gray images. The population is initialized with 10 particles and tested with 100 iterations.

Table 1. Efficiency factor for segmentation of an images

Efficiency fator	Description (formulation)
MAE (Mean Absolute Error)	$MAE = \frac{1}{IJ} \sum X(i,j) - \bar{X}(i,j) $ Here $X(i,j)$ and $\bar{X}(i,j)$ are intensity values of pixel of images with I x,J dimensions.
RMSE (Root Mean Square Error)	$RMSE = \sqrt{MSE}$ Here MSE is Mean Square Error
PSNR (Peak Signal to Noise Ratio)	$PSNR = \frac{10 \log 255^2}{MSE}$ Here MSE is Mean Square Error
NAE (Normalized Absolute Error)	$NAE = \frac{\sum X(i,j) - \bar{X}(i,j) }{\sum X(i,j) }$ Here $X(i,j)$ and $\bar{X}(i,j)$ are intensity values of pixel of images with I x,J dimensions.

Table 2. Comparison based on MAE values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	MAE (PSO)	MAE (CHDPSO Proposed method)
Dog	128.8536	174.0092
Jetplane	105.4983	141.5161
Lena	134.865	190.8294
Peppers	129.5822	190.4533
Walkbridge	122.3561	166.9428

Table 3. Comparison based on RMSE values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	RMSE (PSO)	RMSE (CHDPSO Proposed method)
Dog	9.6058	9.6058
Jetplane	10.7026	10.7026
Lena	10.2300	10.2300
Peppers	10.4152	10.4152
Walkbridge	10.3719	10.3719

Table 4. Comparison based on PSNR values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	PSNR (PSO)	PSNR (CHDPSO Proposed method)
Dog	65.5779	65.5779
Jetplane	63.4155	63.4155
Lena	64.3187	64.3187
Peppers	63.9599	63.9599
Walkbridge	64.0432	64.0432

Table 5. Comparison based on NAE values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	NAE (PSO)	NAE (CHDPSO Proposed method)
Dog	2.1288	2.7310
Jetplane	3.0093	2.2423
Lena	9.3888	3.0152
Peppers	2.7157	3.0331
Walkbridge	2.4048	2.6452

Table 6. Comparison based on MAE values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	MAE (PSO)	MAE (CHDPSO Proposed method)
Dog	114.9711	143.5494
Jetplane	138.4853	173.470
Lena	128.4531	180.5356
Peppers	134.4336	173.6347
Walkbridge	132.1281	158.2975

Table 7. Comparison based on RMSE values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	RMSE (PSO)	RMSE(CHDPSO Proposed method)
Dog	10.0525	9.9051
Jetplane	10.3433	10.0552
Lena	10.2560	10.2621
Peppers	10.3679	10.0316
Walkbridge	10.3567	10.1545

Table 8. Comparison based on PSNR values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	PSNR (PSO)	PSNR(CHDPSO Proposed method)
Dog	64.6689	64.9642
Jetplane	64.0985	64.6635
Lena	64.2681	64.2562
Peppers	64.0510	64.7105
Walkbridge	64.0727	64.4669

Table 9. Comparison based on NAE values of CHDPSO (proposed) method and PSO existing algorithm for two level segmentation

Name of the Image	NAE (PSO)	NAE(CHDPSO Proposed method)
Dog	1.0955	1.4935
Jetplane	1.4103	1.8248
Lena	1.3422	1.8957
Peppers	1.6018	1.8067
Walkbridge	1.4217	1.6613

Tables 2 and 6 compare the existing PSO algorithm with proposed algorithm CHDPSO on the basis of Mean Square Error (MAE). MAE value is less for the proposed CHDPSO algorithm is compared to the existing algorithm which shows that image quality is improved. Tables 3 and 7 similarly compare the existing PSO algorithm with proposed algorithm CHDPSO on the basis of Root Mean Square Error (RMSE). Most of the cases RMSE value is less. The tables 4 and 8 compare the existing PSO algorithm with proposed algorithm CHDPSO on the basis of PSNR since PSNR value is inversely proportional to RMSE so its value will be greater than the existing algorithm which is shown in the table. On the basis of the result obtained from tables 2 to 9, it is verified and tested that the proposed algorithm gives a better result as compared to the existing PSO method.

In the CHDPSO method to find the multi thresholding value cumulative histogram will be used which divide the x-axis of the histogram into K parts. Each K parts for K level of segments which is described in figure 2.

Figure 3 describes the output of the segmented image for different level. The convergence of the algorithm is described by the figures 4 and 5 here x-axis and y-axis used for the number of iterations and fitness value respectively.

Figure 2. Histogram of image

Figure 3. Two Segmented Cumulative Histogram of image

Figure 4. Four Segmented Cumulative Histogram of image

<i>Original Image</i>	<i>Two Segment Image</i>	<i>Four Segment Image</i>

Figure 5. Output Images after segmentation by proposed algorithm

Figure 6. Convergence of CHDPSO method for 2-level of segmentation

Figure 7. Convergence of CHDPSO method for 4-level of segmentation

5. Conclusions

In this study, our aim was to propose a novel Cumulative Histogram Dynamic PSO algorithm. The population is initialized with the help of cumulative histogram. The proposed algorithm is tested and verified by images obtained from Mnist datasets. After comparing the result of Cumulative Histogram Particle Swarm Optimization Algorithm with an existing algorithm gives better results.

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