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Recent Trends and Techniques in Image Enhancement using Differential Evolution- A Survey

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Abstract— ***The Differential Evolution algorithm represents an adaptive search process for solving engineering and machine learning optimization problems. Performance of this algorithm rely on its parameter setting. These parameters are usually constant during the entire search space. Recently each and every field of research is utilizing the properties of DE. One of the very active area of research is image enhancement which is growing very fast. Many researchers have proposed various research papers with enhancement of various parameter by combining DE with different image enhancement techniques. This paper reviews several approaches for contrast enhancement in spatial domain as well as in frequency domain by using DE. The survey leads to the conclusion that field of DE is growing fast and improving the contrast using DE will help to solve many complex problems in Image Processing.***

Keywords— Differential Evolution, Contrast Enhancement, Thresholding, Image Segmentation, Fuzzy System, Particle Swarm Optimization, Genetic Algorithm.

I. INTRODUCTION

With the continuous development of computer science and technology, the field of Image processing is considered as a very active area of research. Digital Image Processing refers to processing of digital images by means of digital computer. The aim is to produce digital images with better contrast and hidden details. To process an input image so that output image will be more suitable, Image Enhancement techniques are required. Image Enhancement refers to highlight some key information in an image and to remove some secondary information which aims to improve the quality of identification in the process at same time [1]. It is characterized as process which includes noise reduction, contrast enhancement, image sharpening operations to produce image of fine quality. Contrast enhancement plays an important role in image processing and in this gray level levels of the input image are mapped to a new set of values so that the histogram of the image becomes flatter to get more homogenous distribution of these gray levels [2].

Recent years many Evolutionary algorithms have been applied to Image Enhancement which include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Differential Evolution and so on. Because DE is a simple search method and performance of convergence is fast, it is more suited for enhancement purpose. The goal of this paper is to provide a state of art survey of image enhancement method based on the DE.

The remainder of this paper is organized as follows: In section II, a brief description of differential evolution algorithm is introduced and section III surveys the various image processing techniques based on DE. The paper ends with specification of conclusion.

II. DIFFERENTIAL EVOLUTION

The Differential Evolution (DE) algorithm is an effective and efficient evolutionary optimization method introduced by Storn and Price in 1995 in order to overcome GAs limitation [3]. Due to its advantages such as simple structure, efficiency, easy implementation, quick convergence, it has gained wide applications in a variety of fields. Like GA, DE has crossover and mutation operators. The main difference between DE and GA is the mutation that makes DE algorithm self-adaptive.

DE creates new candidate solutions by combining parent individual with several other individuals of the same population. DE possesses 3 genetic operators referred to as mutation, crossover and selection. DE initializes with a population of size NP D dimensional parameter target vectors

$$X_{i,G} = \left[X_{1,i,G}, X_{2,i,G}, \dots, X_{D,i,G}\right], i = 1,2,\dots,NP \qquad (1)$$

for each generation G. The parameters of the vectors of the population are uniformly distributed on the intervals $[x_j^L , x_j^U]$.

Trial vector is generated by mutation and crossover operations. Mutant vector is calculated by randomly choosing three individual vectors. Each individual gets a chance to become parent depending on the other randomly selected auxiliary parents. The parents $x_{r1,G}, x_{r2,G}, x_{r3,G}$ are selected such that r1, r2, r3 ∈ {1,2,…NP} and $i \neq r1 \neq r2 \neq r3$. Mutant vector also called donor vector can be derived as follows:

$$v_{i,G} = x_{r1,G} + F * (x_{r2,G} - x_{r3,G}) \qquad (2)$$

where F is the mutation control constant, a positive real valued parameter chosen from the range [0, 2], which controls the amplification of the equation $(x_{r2,G} - x_{r3,G})$. After mutant vector is generated, crossover operation is used to increase the diversity of the donor vectors. Crossover produces a trial vector $u_{i,G}$, by mixing the donor vector and the target vector.

$$u_{ji,G} = \begin{cases} v_{ji,G}, if\ (randj \leq CR)\ or\ (j = j_{rand}) \\ x_{ji,G}, if\ (randj > CR)\ or\ (j \neq j_{rand}) \end{cases} \tag{3}$$

where j= 1,2,..D; randj ∈ [0,1] and in $j_{rand}\ rand \in 1,2,..D$; CR lies in the range [0, 1].

Then the selection operation produces new target vector. If the fitness value of the individual trial vector is greater than the individual target vector, then the new target vector will be the trial vector for the next generation otherwise old target vector will be retained as parent for the next generation. In this way individuals that are more fitted to the environment will be preserved in the population.

III. LITERATURE REVIEW

A. Image Contrast Enhancement

In order to find the global optimum of non-linear, non-convex and non-differentiable function defined in the continuous parameter space, Storn and Price [3] proposed the Differential Evolution algorithm in 1995. Since then DE and its variants emerged as versatile family of the evolutionary computing algorithm and have been applied to successfully solve numerous real world problems. This proposed method converged faster and with more certainty than Adaptive Simulated Annealing.

L.S. Coelho et. al. [12] proposed three differential evolution approaches based on chaotic sequences using logistic equation for contrast enhancement purpose. The objective is to maximize the fitness criterion so as to enhance the contrast and detail in the image by adapting the parameters using contrast enhancement technique. Results are compared with classical DE and showed that the application of chaotic sequences improve the performance of classical DE optimization algorithm.

In 2010, Q. Yang et al. [17] proposed an adaptive image contrast enhancement algorithm based on differential evolution to tune gray transform automatically. Tubbs proposed a regularized incomplete beta function that represent some nonlinear transform functions used in image contrast enhancement. But defining the coefficients of the beta function was a problem. Applying the differential evolution in image contrast enhancement utilized the global quickly search ability of the differential evolution algorithm, adaptive mutation, search, at last searches the optimal α, β values of beta function and get an adaptive contrast enhanced image. To avoid trapping into local optimum, a chaotic differential evolution algorithm was proposed. Experimental results showed that the proposed algorithm can find the global optimal α, β in few iterations and save computational time and complexity.

In 2012, M.C. Lee et al. [21] proposed an automatic image enhancement tool for smart phone by using interactive differential evolution (IDE). From a remarkable progress of the camera sensor in mobile devices, people took pictures with their mobile phone. However, as they were not satisfied with their images, they wanted to edit by using mobile applications, which were complex and cause user fatigue. To reduce it and make a simple interface, author exploited IDE. He proposed color enhancement tool by using IDE. Not only it was simple and convenient, but it also relieved the user fatigue. Five experiments were conducted and twenty people participated in the experiment to evaluate the user satisfaction and fatigue degree. Thirty four images were used for evaluation and comparison. The enhanced images compared with the original and other two images generated by IGA and PE studio. In addition, the best-fit crossover rate was found to reduce the color bias of the images.

In 2014, P.P.Sarangi et al. [26] suggested contrast enhancement of an image by gray level modification using parameterized intensity transformation function that is considered as an objective function. The task of D.E was to adapt the parameters of the transformation function by maximizing the objective function criterion. This criterion defined as fitness function of DE. Experimental results compared with other enhancement techniques, viz. histogram equalization, contrast stretching and particle swarm optimization (PSO) based image enhancement techniques. In all images it is found that DE images contain more detail information than the other methods. Thus the results obtained by DE found better.

In 2014, L.M. Rasdi et.al. [27] proposed an adaptive DE based on chaotic sequences and random adjustment for enhancing the contrast of image. Proposed method evaluated two variations of adaptive DE for application of optimal image contrast enhancement. The first method was DE using chaotic sequences and the second was DE based on random adjustment of the parameters. The objective is to increase the fitness criterion. The results are compared with classical DE which shows that the proposed DE gives best objective function.

In 2016, G.E. Guraksin et al. [34] proposed an underwater enhancement approach by using differential evolution algorithm. Here, the underwater image firstly separated into RGB color components in the sense of the objective of improving underwater images. After that the contrast for each component improved. Then the R, G, B components of the colored image obtained, contrast stretching procedure was performed to these components separately. While improving contrast, differential evolution (DE) algorithm used in order to determine the contrast limits. Differential evolution described limits as a fraction between 0.0 and 1.0. After improving contrast, underwater images sharpened by using unsharp masking and the enhanced version of the underwater image was obtained.

In all these papers, Differential Evolution algorithm used in order to increase the contrast of the image. While improving contrast, this algorithm also determine the contrast limits. Experimental results compared with other enhancement techniques, viz. histogram equalization, contrast stretching, genetic algorithm, particle swarm optimization and found that DE images contain more detail information than other methods.

B. Image Segmentation

S. Rahnamayan et. al. [8] proposed image thresholding based micro Opposition-Based Differential Evolution (micro-ODE). In this approach, micro DE segmented the image into 2 classes by minimizing the dissimilarity between input gray level image and binary image. Then the result was compared with thresholding-method Kittler algorithm which showed that proposed approach is superior to the Kittler algorithm.

S. Fan et. al. [19] presented Infrared Electric image segmentation using Fuzzy Renyi Entropy (FRE) and Chaos Differential Evolution algorithm (CDE). In this paper, the histogram of image is transformed into fuzzy domain and the fuzzy entropy of object as well as background is computed by using Fuzzy Renyi Entropy. Then a chaos DE algo was presented to find the optimum threshold. Results showed that presented method is more effective and less time-consuming.

A.Nakib et. al. [20] presented an enhanced version of the classical DE algo using low-discrepancy sequences and a local serach, called LDE which is used to compute the parameters of Gaussian distribution. Experimental results showed that LDE produces satisfactory result, thus indicating that it can be used for image segmentation in multi-thresholding due to its computational efficiency.

In 2014, S. Paul et. al. [28] proposed a histogram based image compression technique on multi-level image thresholding. Shannon's entropy is maximized to obtain the best threshold. This entropy is maximized using metaheuristic algorithm named Differential Evolution which reduces the computational time and standard deviation of objective value. For comparison and testing, important quality metrics- PSNR, WPSNR and storage size of the compressed image are used.

Ouarda et.al. [29] proposed two approaches PSO and DE to find the optimal thresholds of an image, based on the concept of fuzzy C-partition and maximum entropy principle. Two approaches were compared and results showed that both algorithms are comparable in terms of solution quality when threshold number is small. While when this number increases, PSO and DE provide same results in terms of accuracy and robustness, but in terms of execution time PSO is more efficient.

Y.J. Gong et.al [30] presented a paper which deal with the superpixel segmentation problem using optimization technique DE. The proposed method produce super pixels in a computation time linear to the size of image. Results showed that the proposed algorithm works well on the Berkeley segmentation benchmark in terms of boundary recall, under segmentation error and time overhead.

In 2015, Y. Shi et. al. [31] proposed an improved DE with mutation strategy and adaptive parameter controlling method (MApcDE). This is proposed to overcome the relation between computation time and dimensions. Results showed that this method can get more efficient results when compared with other threshold methods and the computation time is shorten.

These papers proposed DE based image segmentation techniques. Chaos DE algorithm was also used to find the optimum threshold. Results showed that DE reduces the computational time and standard deviation of objective values. Thus DE can be used for image segmentation in multi-thresholding due to its computational efficiency.

C. De Variants

Liu et.al. [6] proposed a new adaptive form of DE having lower no. of search parameters required to be set by the user a priori. Fuzzy Differential Evolution algorithm which uses fuzzy logic to adapt the values of control parameters, the mutation amplification and the crossover constant was proposed. Results showed that for a given objective function value, the FDE algorithm needs less generations than the DE does.

In 2007, Wang et. al. [7] proposed a hybrid differential evolutionary algorithm for global optimization. In this method, population is generated by chaotic systems and its local searches is executed by pattern search technique, which enhance the performance of DE. Experimental results demonstrate that the new algorithm is more effective and efficient.

R. Thangaraj et. al. [10] introduced a new Differential Evolution algorithm based on Adaptive Control Parameters (ACD). Its performance is tested with ten standard benchmark problems and the results were compared with the classical DE in terms of function fitness value, number function evaluations, convergence time and success rate. Experimental results showed that proposed algorithm helps in improving the solution quality as well as convergence rate.

Zhong et. al. [22] presented an algorithm to improve the robustness and efficiency of DE, namely, the stochastic coding DE (SDE). Instead of encoding each individual as a vector of floating point numbers, the proposed SDE represented each individual by using multivariate normal distribution. The multivariate normal distribution is used to evaluate the fitness of individuals and to sample neighboring individuals for local fine-tuning. DE operators are extended to generate offspring. This method investigated by nine benchmark functions and results showed that SDE offers a very promising performance.

Wang et. al. [32] proposed fuzzy-based adaptive method for crossover rate values to improve the convergence rate of DE. Depending on two factors of the evolutionary environment, the change rate of solution of center of solutions and the density of each dimension, CR values decided. This method was tested by CEC2015 and compared with fuzzy adaptive DE (FADE). The results expressed that the distributed CR values have better performance than focus on a certain CR values.

In 2016, Zhou et. al. [36] proposed DE with multi-stage strategies (DEMS) for global optimization. The evolution process of DE is divided into multiple stages according to the average distance between each and every individual in the initial population. At the beginning of each generation, each individual's average distance is calculated to determine the evolution stage. Then in the current population for each target vector, a mutation strategy is randomly selected to produce a offspring vector. The results verify the proposed algorithm can balance the exploration and exploitation.

Thus in order to improve the convergence rate of DE, different DE variants are proposed. Experimental results showed that proposed methods help in improving the solution quality, convergence rate, and are more effective and efficient.

D. Other Fields:

In 1997, P. Thomas et. al. [5] presented the application of the DE to the task of image registration. Image registration is used to match two or more images. In order to effect the registration of 2 images a transformation must be found which enables one image to be transformed with respect to other, so that the corresponding points in the image coincident. The DE is effective and powerful algorithm with few control parameters and here is used to minimize the fitness metric. This approach performs the least square error solution.

In 2008, A. Basturk et. al. [11] presented DE algorithm based cellular neutral network (CNN) for edge detection in digital images. Results indicate that the proposed CNN operator outperforms other edge detectors and gives superior performance in edge detection in digital images.

In 2010, Jinsung Oh et. al. [15] presented a new morphology-based homomorphic filtering technique for feature enhancement in medical images. This method is based on decomposing an image into morphological subbands. By using the morphological subbands, homomorphic filtering is performed. DE is used to find an optimal gain and structuring element for each and every subbands. Results showed that proposed filter improved the contrast of the features in medical images.

V. Aslantas et. al. [16] introduced a novel optimal method for multi-focus image fusion using differential evolution algorithm. DE was employed to optimize the block size with the objective of maximizing the sharpness of the fused image. This method decomposes the source defocused images into blocks and then selects the block with higher sharpness. These selected blocks are then combined to form the fused image. Results showed that DE based method outperforms the Laplacian pyramid and the wavelet based methods in terms of objective evaluation criteria and subjective analysis.

Ahmadipour et.al. [35] presented a method for multiple human detection in the image by using DE algorithm in order to improve window position detection speed and HOG-LBP algorithm for feature extraction.

Thus DE is growing fastest in every area of research which include image watermarking, image registration, filtering techniques, detection techniques, microwave imaging. Experimental results verified that the proposed method gives superior performance in these fields.

Table A: De In Image Contrast Enhancement

DE variant and other method	Author, year	Application, Advantages	Experimental Parameters
DE	R. Storn et. al. [4], 1997	Converged faster and with more accuracy.	
DE combined with chaotic sequences	L.S Coelha et. al. [12], 2009	Maximizes the fitness criterion for enhancing the contrast and detail in the image	F=0.5, CR=0.8, NP=10
Chaotic DE algo	Yang et. al. [17], 2010	Enhance the contrast of an image and reserve detail information of the target	F=0.85, CR= 0.9
Interactive DE (IDE)	M.C. Lee et. al. [21], 2012	Simple, convenient, having best fit crossover rate	CR=0.3
DE	P.P.Sarangi et. al. [26], 2014	Achieved best detail content in the image	CR=0.5
Adaptive DE based on chaotic sequences and random adjustment	L.M. Rasdi et. al. [27], 2014	Maximize pixels in the edges of image and increase the entropy	F=0.9, CR=0.3, NP=20
DE	G. E. Guraksin et. al. [34], 2016	Improved contrast of underwater image in RGB component	F=0.8, CR=0.8, NP=40.Gmax=1000

Table B: De In Image Segmentation

DE variant and other method	Author, year	Application, Advantages	Experimental Parameters
Micro Opposition based DE	S. Rahnamayan et. al. [8], 2008	Faster than micro DE, superior to Kittler algo.	F=0.9, CR=0.9, NP=50
Chaos DE (CDE) and Fuzzy Renyi Entropy	S. Fan et. al. [19], 2011	Effective and feasible	
Hybrid DE with low discrepancy sequences (LDE)	A. Nakib et. al. [20], 2012	Effective due to its quality performance	
DE	S. Sarkar et. al. [25],	Improved the computational	

	2013	efficiency and having more accuracy	
DE	S. Paul et. al. [28], 2014	Reduce the computational time and standard deviation of objective value	F=0.5, CR==0.95
DE and PSO in Fuzzy C-partition	A. Ouarda et. al. [29], 2014	Reduce the time complexity	
DE	Gong et. al. [30], 2015	Works well in terms of boundary recall, time overhead, error	
IDE with adaptive parameter control strategy	Y. Shi et. al. [31], 2015	Improved convergence rate	F=0.5, CR=0.3 NP=20

Table C: De Variants

DE variant and other method	Author, year	Application, Advantages
Fuzzy DE algo (FDE)	Liu et. al. [6], 2002	More efficient and needs less generation than classical DE
DE based on adaptive control parameters (ACDE)	R. Thangaraj et. al. [10], 2009	Improved the solution quality and convergence rate
Stochastic Coding DE (SDE)	Zhong et. al. [22], 2012	Effectiveness and efficiency of SDE
Self-adaptive DE (SDE)	A.Ghosh et. al. [23], 2013	Improved results in terms of accuracy and kappa coefficient.
Fuzzy inference system with DE	Wang et. al. [32], 2016	Convergence improved

Table D: Other Fields

Area	DE variant and other method	Author, year	Application, Advantages	Experimental Parameters
Image registration	DE	P. Thomas et. al. [5], 1997	Outperforms least square error solution and has few control parameters	
Image watermarking	DE	V. Aslantas et. al. [9], 2008	Improvement in transparency and robustness	F=0.6, CR=0.8, NP=150, Gmax=400
Edge detection	Cellular Network optimized by DE algo	A. Basturk et. al. [11], 2009	Outperforms other edge detectors and offers superior performance.	
Microwave imaging	DE based iterative multi-scaling algorithm	M. D Onelli et.al. [14], 2010	Accurate reconstruction and improvement over DE algo	F=0.6, CR=0.8, NP=3000
Feature enhancement	Morphology-based Homomorphic filter and DE algo	Jinsung et.al. [15], 2010	Improved the contrast of the features in medical images	F=0.5, CR=0.5, NP=5,Gmax=50
Multi-focus image fusing	DE	V. Aslantas et. al. [16], 2010	More robust, stable, reliable	F=0.9, CR=0.6, NP=10, Gmax=50
Moving object detection	Markov Random field and distributed DE	A. Ghosh et. al. [24], 2013	Provide better segmented results, identify locations of the moving objects, less computation intensive.	
Detection technique	DE and HOG-LBP	Admadipour et. al. [35], 2016	Detect proper windows faster and having higher precision on INRIA	

IV. CONCLUSION

The DE family of algorithms meant for global numerical optimization over the continuous search spaces. It has gained wide applications in a variety of fields due to its advantages such as simple structure, efficiency, easy implementation, quick convergence. This field has been greatly enriched by the efforts of researchers from various domains. DE combined with other image techniques like thresholding, fuzzy set etc. give significantly improved results. In this article, we made an effort to outline the state-of-the-art research on DE over the years and came to conclusion that the field of DE is growing fastest in every area of research. Thus DE is considered as a very powerful technique which can be utilized efficiently in the field of image enhancement.

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