Image optimization

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Abstract

Image contrast enhancement by optimizing entropy of image.

The fundamental method of image enhancement is using an intensity transformation function to increase the information content of the enhanced image. In the current study, a parameterized transformation function is employed, utilising both local and global picture information. Here, entropy from the image are taken into account by an objective criterion for quantifying image enhancement. By using GA to optimise the parameters utilised in the transformation function, we attempted to provide the best augmented image in accordance with the objective criterion. Results are contrasted with those obtained using contrast —–, ——-, and ——- image improvement techniques.

Keywords: Image processing, Image enhancement, Optimization

1. Introduction

There are several parameters involved in an image enhancement technique....(write about image enhancement after introducing all the algo below)

Genetic algorithm is an optimization technique which follows Mendel's theory of evolution.Initially from a given population it selects the parents using different selection operators like tournament selection, Roulette wheel selection, proportionate selection, Rank selection, steady selection and so on. After selection of parents crossover is done using crossover techniques(ex: binary crossover) between them to exchange gene information and then mutation is done for introducing better characteristics in children. Until we receive a better set of solutions or children we keep on repeating the process.Therefore this approach is continued further for better set of solutions.

2. Related Work

Image enhancement can be done in various ways. And in [1] the hue is kept constant and using adaptive contrast enhancement along with particle swarm optimization these four functions are maximized i.e. the entropy, image exposure, histogram flatness and histogram spread.

In [2] a new approach for gray scale image enhancement is shown. Mainly the contrast is enhanced using unsharp masking techniques. The functions introduced here are same as the previous paper, but here advanced gravitational search algorithm is used to find the force which relates with velocity and the acceleration of the particle. Hence this convergence with the classical particle swarm optimization gives a better result here.

The evolutionary algorithm like particle swarm optimization is used in multiple ways in image enhancement. Like in [3] the quality of intensity image is improved where the objective function contains the entropy and edge information of image. The enhanced image is formed with the help of scaling but that sometimes results in gamut problem. To remove the problem rescaling of saturation component is done here.

In all the papers till now we have seen enhancement in either contrast or entropy, histogram flatness and so on .But one of the most challenging enhancement is shown in [4], denoising of magnetic resonance image i.e. removing the impulse noise and Rician noise in the medical MR images. They are removed by using a bilateral filter that utilizes the Enhanced grasshopper optimization algorithm (EGOA) in parameter optimization. And now in this digital image era high quality images are in high demand but low light images have a narrow dynamic range which needs to be enhanced. An image sensor under the insufficient light might not work due to this drawback. In [5] the author presents the low light enhancement with the help of variational-optimization-based Retinex algorithm. It uses gamma corrected version to constrain the illumination component, the whole method gives the better result without saturation, noise amplification and colour distortion. Further in [6] image enhancement is done using ant colony optimization technique.

Here in [7] genetic algorithm(GA) is used for optimization.Most of the medical images have very low contrast or full of noise and the challenge is to sharpen them and make them easier in processing and due to large solution space of GA, noise was reduced and the contrast of medical image has increased so resulted image become more readable.Here the author conducts several experiments taking different inputs and applying simultaneous selection types like Roulette Wheel selection, Tournament selection and Rank selection on mean square error(MSE), Peak Signal to Noise Ratio(PSNR) and Structural Similarity Index Measure(SSIM). After every crossover and mutation it gave the best result in case of Tournament selection. In [8] author shows a survey that regular growth of GA due to its large sampling solution space . And hence one of its applications is image enhancement i.e. removing noise and amplifying contrast and other parameters. Further in this paper they show application of GA in image segmentation and image pre-processing. Further in [9] multiobjective genetic algorithm is used for image enhancement. Here benchmark images are used for image enhancement. The multiobjective GA optimizes the intensity, entropy and number of edges and it results in automatic image enhancement. Via real coded GA, Intensity Edge and Entropy Algorithm(IEEALGO) is proposed by the author.

[10]Here, entropy and edge information from the image is taken into account by an objective criterion for quantifying image enhancement. By using PSO to optimize the parameters utilized in the transformation function, we attempted to provide the best-augmented augmented image in accordance with the objective criterion.

An overview of the genetic algorithm for greyscale image improvement using N-point Crossover is presented in this study[11]. The author deals with issues like contrast increment, noise and blurring removal, and detail illumination as examples of enhancement operations.

[12]This study discusses the tasks of picture pre-processing and provides a brief description of the canonical genetic algorithm. The definitions of image enhancement and image segmentation, as well as the reasons why these processes are necessary and how genetic algorithms can be used to improve and segment images, are all covered in this paper.

For both bimodal and multimodal images, the efficiency of GAs in the automatic selection of an ideal image enhancing operator is demonstrated in this paper[13]. The program can choose the best enhancement function without iterative visual contact or prior knowledge of image statistics. Experimental evidence supports the algorithm's convergence. Despite the fact that fuzziness measurements have been employed as fitness values, alternative metrics may be employed based on the issues.

[14]The fundamental ideas and typical picture enhancement methods will all be thoroughly covered in this study. The research focuses on spatial domain image enhancing techniques, namely point processing techniques and histogram processing.

[15]This study suggests a technique for improving the contrast of a grayscale images using a genetic algorithm that gauges an individual's fitness by assessing the strength of the spatial edges present in the image. An association between input and output grayscale levels is discovered using the genetic algorithm's capacity to search for a solution in a global space, transforming an initial grayscale image into an improved image with strong contrast.

[16]Obtaining an improved approach that maintains the original brightness is the main goal of this paper. This approach, which works with all kinds of pictures, including low contrast MRI brain images, includes a control on the amount of contrast enhancement. The fundamental concept behind this technique is to divide the input image histogram into two subhistograms based on a threshold that is determined by Otsu's optimality principle. In order to fulfill the aforementioned objectives, a bicriteria optimization problem is then created. Optimal contrast enhancement parameters are chosen for the subhistograms, and when combined, they result in an output image with improved contrast and maintained features.The contrast of the input image is improved by this approach more effectively than by current HE techniques.The augmented brain image's high quality suggests that it can be effectively used for brain cancer diagnosis in subsequent processes like segmentation and classification. Contrast enhancement quantifiable measurements like discrete entropy and a natural image quality evaluation provide strong evidence for the performance of the suggested technique.

[17]The mean brightness with maximum entropy (BPHEME), which can be preserved in a continuous view, is a novel case of histogram specification that is discussed in this study. Using a variational technique, BPHEME aims to choose the best histogram that, given the mean brightness requirement, has the highest differential entropy, and then executes the histogram specification using the guidance of that chosen histogram.

[18]This article suggests a useful technique for improving contrast and histograms in digital photos. Here, an automatic transformation method is provided for enhancing dimmed images' brightness by gamma correction and probability distribution of luminance pixels. The suggested image enhancement solution employs temporal information about the variations between each frame to improve video while minimising computer complexity. Ac-

cording to experimental findings, the suggested method generates improved images of an equal or greater quality than those generated by earlier state-of-the-art techniques.

[19]This study introduces a novel ACE (Adaptive Contrast Enhancement) algorithm that solves the issues with traditional methods such as noise over enhancement and ringing effects. First, by extending Hunt's picture model, a mathematical model for the LSD(Local Standard Deviation) distribution is put forth. The CG(Contrast Gain) is thereafter developed as a function of the LSD. The transformation between the LSD histogram and a desired LSD distribution determines the nonlinear function. It can be demonstrated using this formulation that traditional ACEs compute the new CGs using linear functions. A good CG is produced by the suggested nonlinear function, which results in low noise over amplification and fewer ringing artefacts. Finally, simulations employing a few X-ray images are offered to show how well the new approach works.

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[31]lastTo assess the efficacy of enhancing grayscale and colour images, respectively, two novel objective functions based on the normalised incomplete beta transform function are proposed in this study. The quantum-behaved particle swarm optimization estimates the transform function parameters using these goal functions (QPSO). Also suggested was an enhanced QPSO with adaptive parameter control. On a number of benchmark grayscale and colour photos, the QPSO and AQPSO methods, as well as the genetic algorithm (GA) and particle swarm optimization (PSO), are put to the test. The outcomes demonstrate that the QPSO and AQPSO outperform GA and PSO for the enhancement of these images, with the AQPSO having certain advantages over QPSO because of its adaptive parameter management technique.

3. Transformation function with Objective

In paper [1]they have used Particle swarm optimization and the transformation, $T(i,j)$ function is:

$$T(i,j) = \frac{g(i,j)}{j(i,j)}[f(i,j) - c * m(i,j)] + m^a(i,j) \tag{1}$$

In paper [2] same transformation function is used as in equation 1.Here there saturation is enhanced using the function

$$S'(x) = [S(x)]^{(1-0.5*exposure)}$$

In here the proposed method is Hybrid (GSA-PSO) Gravitational search algorithm and particle swarm optimization.entropy,histogram spread and histogram flatness measure is increased using the above method.

We have considered two transformation functions for enhancing the image contrast based on two parameters.

$$T(i,j) = \frac{g(i,j)}{j(i,j)}[f(i,j) - c * m(i,j)] + m^a(i,j) \tag{2}$$

In the other transformation, we first normalize the image in the range [0, 1] and then apply the transformation.

$$N(i,j) = \frac{f(i,j}{255}$$

$$T(i,j) = param1 * (N(i,j) * *param2) \tag{3}$$

We then rescale the image and clip it between 0-255.

$$T(i,j) = T(i,j) * 255.0 \tag{4}$$

A comparison for both the methods will be provided in the later parts of the paper.

4. Problem statement

We try to enhance the contrast of the image using different image quality parameters, these include entropy, histogram flatness measure, histogram spread and edge density.

$$Entropy = -\sum p(i) \log_2 p(i)$$

where, $p(i)$ is the probability of occurrence of i^{th} intensity level.

$$HS = histogramspreadformulalikhnahai$$
$$HFM = histogramflatnessformulalikhnahai$$

Our objective function is:

$$maximize \quad Entropy * HFM * HS * (1 + EdgeDensity) \tag{5}$$

$$p(i) = \frac{n_i}{M \times N} \tag{6}$$

where, n_i denotes number of pixels with value i and $M \times N$ denotes the dimension of the image.

5. Proposed model

We experimented with taking up different combinations of image and parameters for running genetic algorithm.

- We considered image, a and c as part of the chromosome and ran GA.
  - Each

5.1. Image Enhancement

5.2. Optimisation

5.2.1. Entropy

Entropy represents the information content in an image. If all the pixels fall in a short range of pixels then entropy would be low while spread out histogram makes the entropy value higher. Entropy is given by

$$Entropy = -\sum p(i) \log_2 p(i) \tag{7}$$

where, $p(i)$ is the probability of occurrence of i^{th} intensity level.

$$p(i) = \frac{n_i}{M \times N} \tag{8}$$

where, n_i denotes number of pixels with value i and $M \times N$ denotes the dimension of the image.

5.2.2. Histogram Spread

Histogram Spread signifies how spread out are the pixel values in the histogram.

5.2.3. Fitness Function

Fitness function measures the fitness of each individual of the population for each generation. We are trying to maximise entropy, sop our fitness function would calculate entropy of the image.
Entropy, E of the image is calculated using equation 5

$$E = -\sum p(i) \log_2 p(i)$$

6. Methodology

6.1. Representation

For image reconstruction purposes, image encoding is needed and although we can use image encoding here as well, our goal here is to particularly enhance the image. Since we have considered parameters which we use to transform the image, and those parameters alone can give us the new image, we skip encoding the image. We encode parameters a(italic) and c(italic) as real numbers.

6.2. Initialisation

We generate chromosomes equal to population size by using a random number generator.

1 Initialise the population by randomly generating param1 and param2

2 randomise image as follows image = f(i, j) + rand(-50, 50)

3 Clip image in the range 0-255

4 add the tuple (image, param1, param2) in the population

6.3. GA Iteration

Now we loop over generations and perform crossover, mutation and generate offspring. The mechanisms for crossover and mutation

6.3.1. Selection

We keep the best 10% fit members of the current generation as elites, i.e., elitism ration of 0.1. We calculate the probability of selection of an individual as a parent using the below formula

$$p = \frac{fitness_i}{\sum fitness_i}$$

where $fitness_i$ represents fitness of i^{th} individual. We generate an array of indices of length $population\_size - num_{elites}$ based on randomly selecting the individuals based on the probabilities obtained.

GAs use a selection mechanism to select individuals from the population to insert into a mating pool. Individuals from the mating poo l are used to generate new offspring , wit h the resulting offspring forming the basis of the next genera tion. As the individuals in the mating pool are the ones whose genes are inherited by the next generation, it is desirable that the mating pool be comprised of "good" individuals. A selection mechanism in GAs is simply a process that favors the selection of better individuals in the populat ion for the mating pool. The selection pressure is th e degree to which the better individuals are favored: the higher the select ion pr essure, the more the better individuals are favored. This selection pressure drives the GA to improve the population fitness over succeeding generations. The convergence rate of a GA is largely determined by the select ion pressure, wit h higher selection pressures resulting in higher convergence rat es. GAs are able to identify optimal or near-optimal solutions under a wide range of select ion pressure [5]. However, if the selection pressure is to o low, the convergence rate will be slow, and the GA will unnecessarily take longer to find the optima l solution. If th e select ion pressure is too high, there is an increased chance of the GA prematurely converging to an incorrect (suboptimal) solution. Tournament selection provides selection pressure by holding a tournament among S competitors, with S being the tournament size. The winner of the tournament is the individual wit h the highest fitness of the S tournament competitors. The winner is then inserted into the mating pool. The mating pool, being comprised of tournament winners, has a higher average fitness than the average population fitness. T his fitness difference provides the selection pressure , which drives the GA to improve the fitness of each succeeding generation . Increased select ion pressure can be provided by simply increasing the tournament size s, as the winner from a larger tournament will, on average, have a higher fitness than the winner of a smaller tournament.

6.3.2. Crossover

Crossover is a genetic operator used in genetic algorithms to vary the population of chromosomes from generation to generation.

We use two point crossover as the genetic operator. In two-point crossover, two crossover points are selected on the parent organisms. Everything between these points is swapped between the parent organisms, rendering two offspring.
Parent 1:

$$11111|22222|33333$$

Parent 2:

$$55555|66666|77777$$

Offspring 1:

$$11111|66666|33333$$

Offspring 2:

$$55555|22222|77777$$

6.3.3. Mutation

Mutation is a genetic operator used in genetic algorithms to maintain genetic diversity from one generation of a population to the next. It is analogous to biological mutation and introduces small, random tweaks in the chromosome, which create diversity and prevent the population from stagnating.

In the mutate function, a random number between 0 and 1 is generated. If this number is less than 0.1 (i.e., there's a 10% chance), a small random value (drawn from a standard Gaussian distribution and scaled down by a factor of 0.1) is added to the a or b parameter of the chromosome.

This form of mutation introduces variability in the population by adding a small amount of noise to the parameters. The noise is drawn from a Gaussian distribution, which is a common choice for this kind of mutation because it tends to generate small changes most of the time (due to the nature of the Gaussian distribution), but occasionally generates larger changes. This allows the genetic algorithm to explore the parameter space by making small adjustments to the parameters, but also gives it the flexibility to make larger jumps occasionally.

7. Conclusion

References

[1] O. P. Verma, P. Gupta, S. Bansal, A. Bansal, Low contrast color image enhancement using particle swarm optimization, International Journal of Information Systems & Management Science 2 (2) (2019).

[2] A. Sharma, R. K. Kapur, Image enhancement using hybrid gsa—particle swarm optimization, in: 2016 2nd International Conference on Contemporary Computing and Informatics (IC3I), IEEE, 2016, pp. 698–704.

[3] A. Ghosh, A. Gorai, Hue-preserving color image enhancement using particle swarm optimization, in: Integration of Swarm Intelligence and Artificial Neural Network, World Scientific, 2011, pp. 157–178.

[4] V. Anoop, P. R. Bipin, Medical image enhancement by a bilateral filter using optimization technique, Journal of medical systems 43 (8) (2019) 1–12.

[5] S. Park, S. Yu, B. Moon, S. Ko, J. Paik, Low-light image enhancement using variational optimization-based retinex model, IEEE Transactions on Consumer Electronics 63 (2) (2017) 178–184.

[6] K. Gupta, A. Gupta, Image enhancement using ant colony optimization, IOSR Journal of VLSI and Signal Processing 1 (3) (2012) 38–45.

[7] F. M. Abdelghader, et al., Medical image enhancement using genetic algorithm, Ph.D. thesis, Sudan University of Science & Technology (2017).

[8] M. Paulinas, A. Ušinskas, A survey of genetic algorithms applications for image enhancement and segmentation, Information Technology and control 36 (3) (2007).

[9] D. P. Singh, A. Khare, Evolutionary image enhancement using multi-objective genetic algorithm, International Journal of Image, Graphics and Signal Processing 6 (1) (2013) 61.

[10] A. Gorai, A. Ghosh, Gray-level image enhancement by particle swarm optimization, in: 2009 world congress on nature & biologically inspired computing (NaBIC), IEEE, 2009, pp. 72–77.

[11] S. Shrivastava, A. Upadhyay, Image enhancement using genetic algorithm, Internaltional Journal of Engineering Research & Technology (IJERT) 3 (5) (2014) 1768–1772.

[12] K. R. Hole, V. S. Gulhane, N. D. Shellokar, Application of genetic algorithm for image enhancement and segmentation, International Journal of Advanced Research in Computer Engineering & Technology (IJARCET) 2 (4) (2013) 1342.

[13] S. K. Pal, D. Bhandari, M. K. Kundu, Genetic algorithms for optimal image enhancement, Pattern recognition letters 15 (3) (1994) 261–271.

[14] R. Maini, H. Aggarwal, A comprehensive review of image enhancement techniques, arXiv preprint arXiv:1003.4053 (2010).

[15] F. Saitoh, Image contrast enhancement using genetic algorithm, in: IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No. 99CH37028), Vol. 4, IEEE, 1999, pp. 899–904.

[16] P. Babu, V. Rajamani, Contrast enhancement using real coded genetic algorithm based modified histogram equalization for gray scale images, International Journal of Imaging Systems and Technology 25 (1) (2015) 24–32.

[17] C. Wang, Z. Ye, Brightness preserving histogram equalization with maximum entropy: a variational perspective, IEEE Transactions on Consumer Electronics 51 (4) (2005) 1326–1334.

[18] S.-C. Huang, F.-C. Cheng, Y.-S. Chiu, Efficient contrast enhancement using adaptive gamma correction with weighting distribution, IEEE transactions on image processing 22 (3) (2012) 1032–1041.

[19] D.-C. Chang, W.-R. Wu, Image contrast enhancement based on a histogram transformation of local standard deviation, IEEE transactions on medical imaging 17 (4) (1998) 518–531.

[20] C. Munteanu, A. Rosa, Gray-scale image enhancement as an automatic process driven by evolution, IEEE transactions on systems, man, and cybernetics, part B (cybernetics) 34 (2) (2004) 1292–1298.

[21] S. Arya, S. Khan, D. Kumar, M. Dutta, P. Lehana, Image enhancement technique on ultrasound images using aura transformation, International Journal in Foundations of Computer Science & Technology 2 (3) (2012) 1–10.

[22] R. Aedla, G. S. Dwarakish, D. V. Reddy, Satellite image contrast enhancement algorithm based on plateau histogram equalization, in: 2014 IEEE REGION 10 SYMPOSIUM, 2014, pp. 213–218.

[23] I. A. Humied, F. E. Abou-Chadi, M. Z. Rashad, A new combined technique for automatic contrast enhancement of digital images, Egyptian Informatics Journal 13 (1) (2012) 27–37.

[24] R. Poli, S. Cagnoni, Evolution of pseudo-colouring algorithms for image enhancement with interactive genetic programming, Cognitive Science Research Papers-University OF Birmingham CSRP (1997).

[25] G. Ramponi, N. K. Strobel, S. K. Mitra, T.-H. Yu, Nonlinear unsharp masking methods for image contrast enhancement, Journal of electronic imaging 5 (3) (1996) 353–366.

[26] F. Saitoh, Image contrast enhancement using genetic algorithm, in: IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No.99CH37028), Vol. 4, 1999, pp. 899–904 vol.4.

[27] Gray-level transformations for interactive image enhancement, Mechanism and Machine Theory 12 (1) (1977) 111–122, special Issue: Robots and Manipulator Systems.

[28] B. Tang, G. Sapiro, V. Caselles, Color image enhancement via chromaticity diffusion, IEEE Transactions on Image Processing 10 (5) (2001) 701–707.

[29] G. Gupta, Algorithm for image processing using improved median filter and comparison of mean, median and improved median filter, International Journal of Soft Computing and Engineering (IJSCE) 1 (5) (2011) 304–311.

[30] G. Raju, M. S. Nair, A fast and efficient color image enhancement method based on fuzzy-logic and histogram, AEU-International Journal of electronics and communications 68 (3) (2014) 237–243.

[31] X. Su, W. Fang, Q. Shen, X. Hao, An image enhancement method using the quantum-behaved particle swarm optimization with an adaptive strategy, Mathematical Problems in Engineering 2013 (2013).