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ENHANCING THE MEDICAL IMAGES QUALITY USING ADAPTIVE GENETIC ALGORITHM

C. Srivenkateswaran[1], K. Regin Bose[2], Belwin J.Brearley[3] and D.C. Jullie Josephine[4]

[1,2]*Department Artificial Intelligence and Data Science, Rajalakshmi Institute of Technology, India*

[3]*Department of Electrical and Electronics Engineering, B.S.Abdur Rahman Crescent Institute of Science and Technology, India*

[4]*Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, India*

Abstract

It is obvious that there is a need for a Medical Decisiveness Determine System (MDDS) should be able to diagnose abnormalities in medical imaging. This is because the medical diagnosis system in health care sectors requires assistants to serve as secondary opinions for medical practitioners. During the process of picture acquisition, it is common practice to adjust the contrast level of medical images in order to prevent image degradation. Contrast enhancement in medical images is typically seen as an optimisation problem, and the Adaptive Genetic Algorithm (AGA) algorithm is utilised in order to arrive at the best possible answer. The findings of the comparison are established between the Adaptive Genetic Algorithm that has been proposed and other algorithms that are already in existence. A number of different performance indicators, including PSNR, SSIM, MSSIM, IFC, VIF, VSNR, MSE, SDME, and NAE, are utilised in order to make comparisons between the results. Methods that have been developed and those that already exist are evaluated using a variety of cancer pictures. As a result, the contrast and quality of medical images can be improved through the utilisation of AGA, which also offers a higher contrast level of medical images, hence facilitating improved decision-making by medical professionals.

Keywords:

MDDS, AGA, SDME, Medical Images

1. INTRODUCTION

An image enhancement technique known as contrast enhancement is a technique that improves the contrast nature of an image by adjusting the dynamic range of the pixel intensity distribution [1]. There are a number of fields that make use of contrast enhancement, including pattern recognition, computer vision, and digital image processing. On the other hand, when it comes to applications that take place in the real world, the images typically meet with anomalous brightness or poor contrast nature. This is caused by a variety of circumstances, including inadequate image acquisition and a lack of imaging device capabilities. The contrast quality is either inappropriate or diminished as a result of the high or low illuminance intensity that occurs during the capture of scenes. An image with a low contrast level has a negative impact on digital image applications, such as image analysis, digital printing, and object recognition, amongst others. This is in addition to the fact that the visual quality of the image is diminished. As a result, it is of the utmost importance to enhance the contrast characteristics of a reference image that has been warped.

Over the past few years, the spatial distributions have been incorporated into the process of image contrast enhancement, with the intensities of the pixels serving as its mapping function [2]. This helps to improve the visual quality of an image and gives promising image quality with decreased distortions; nevertheless, the contrast nature of an image is severely harmed as a result of this phenomenon. The enhancement strength limit is insufficient, which causes the spatial distribution to function poorly. Additionally, the presence of noise in low-light images [3] requires some optimisation through the use of advanced approaches. This issue could be overcome by applying the principles of machine learning or deep learning [4].

Due to the fact that the image enhancement approach is based on the contrast enhancement process, the existence of colours that are not realistic can be beneficial in applications that require perceptually better colours and have more recognised texture features. As was previously explained, these applications combine surveillance by making use of improved visual perception. despite the fact that there are a great many approaches that can be utilised to carry out these responsibilities, each of which has both pros and disadvantages involved.

The histogram equalisation approach is frequently utilised in the process of image contrast enhancement due to the fact that its implementation process is both quicker and simpler. Maintaining the optimal characteristics of the histogram equalisation approach is the primary objective of the current research, and in order to do this, various enhancements have been implemented in order to circumvent the limits. In light of this, the equalisation process that is based on bi-histogram segmentation is utilised in order to preserve the brightness of the image while dealing with its contrast nature.

The primary goals of the research effort are as follows: The primary goal of the study is to improve the contrast nature of an image for the purpose of making it more suiTable.than the original reference image. The process of image enhancement is a collection of procedures that tries to improve the visual representation of a reference image or to convert an image into a suiTable.for image analysis produced by a computer or a person. Both of these goals are accomplished via the process of image enhancement. For the purpose of developing an Adaptive Genetic Algorithm technique to enhance the contrast nature of an image while taking into consideration the limits connected with processed images, this includes the preservation of brightness and the appearance of naturalness.

2. LITERATURE SURVEY

This technique has resulted in the development of a revolutionary contrast enhancement algorithm that is dependent on histogram equalisation. This algorithm is referred to as the triple dynamic clipped histogram levelling strategy. The histogram of the input image is first divided into three sections, in

accordance with the mean or the centre, in the method that has been devised. Once this step has been completed, the technique for trimming the histogram is carried out in each sub-histogram. Last but not least, before the rectification operation of each sub-histogram is carried out independently, each sub-histogram is mapped to a different dynamic range. The technique that was designed is capable of accomplishing a number of goals, including the most extreme normal data content (entropy), enhancement rate control, and reasonable brightness protection. Furthermore, this technique encourages frequent enhancement by offering clear images and conserving the most extreme places of interest while simultaneously delivering clear images. As far as the entropy, basic closeness list, and visual quality based on Mean Opinion Score (MOS) are concerned, the execution evaluation of the proposed strategy reveals that the developed algorithm has a higher prevalence when compared to the strategies that have been recently presented.

A version of the low contrast enhancement algorithms that rely on the Singular Value Decomposition (SVD) for the purpose of preserving the average brightness of a particular image is presented in [6]. In spite of the fact that the SVD-based procedures are able to enhance the low-complexity images by scaling their particular esteem framework, it is possible that they are unable to give tasteful results for some low-contrast images. It is possible to obtain the single value grid of the balanced image by utilising the suggested technique, which involves determining the weighted total of certain networks of the input image and its Global Histogram Equalisation (GHE) image. Recreation outcomes suggest that the established technique safeguards the image brightness all the more definitely and upgrades it with fairly unimportant visual antique oddities. The classic methods of picture equalisation, such as GHE and Local Histogram Equalisation (LHE), as well as the SVD processes, which are based on scaling its particular esteem both subjectively and numerically, are defeated by this method.

[7] presents a competent method that is capable of providing food with the restriction of over enhancement while also providing the highest possible level of entropy protection. In the technique that was developed, the histogram of the input image is first segmented based on the valley places of the image, and then a weighted conveyance is connected to all of the fragmented sub histograms. This is followed by the histogram levelling, gamma revision, and homomorphic separation processes. When it comes to visual quality, as well as the largest entropy conservation and complexity enhancement, the results show that the created approach external performs better than other conventional histogram equalisation systems.

by designating whole unique range to restrict gone portions formed after division process, and each fragment is balanced freely, [8] established a technique that maintains a strategic distance from un-even development of intensities. This approach was developed in order to maintain a strategic distance. In addition, it is recommended that intensities be standardised in order to achieve the ultimate goal of preserving a strategic distance from the intensity saturation problem.

Within the scope of [9], an efficient complexity improvement strategy that is dependent on evolutionary algorithm was devised. For the purpose of enhancing the contrast characteristic of an image, this technique employs a straightforward procedure.

Based on the experiments that were shown before, it is clear that various imagegraphs can be improved by employing image contrast techniques. Soft computing strategies, which are used to improve the contrast nature of images, are superior to other histogram equalisation and numerical techniques in terms of their ability to improve image quality. Based on the findings of these investigations, it is clear that a variety of performance metrics are utilised in order to evaluate the quality of a contrast enhanced reference image.

3. PROPOSED METHOD

The purpose of the proposed research is to improve the contrast level of medical pictures by employing a method for image contrast enhancement that addresses the issues that are currently present in the existing body of relevant literature. The proposed method makes use of an optimisation algorithm or adaptive optimisation methodology known as the Adaptive Genetic Algorithm (AGA), which is specifically utilised to expand the contrast range of images in wireless capsule endoscopy. This is done in order to tackle the issues that are associated with contrast augmentation.

In order to improve the contrast features of a picture, the planned research project that makes use of AGA will initially use the capture of images by wireless capsule endoscopy. Through the use of AGA, the proposed method is able to successfully improve the contrast nature of wireless capsule endoscopy images, which ultimately results in a greater accuracy rate.

3.1 ADAPTIVE GENETIC ALGORITHM

A genetic algorithm is a programming technique that makes use of biological evolution to solve the issues that are associated with improving image contrast. This technique is also considered to be an optimisation method that effectively solves the issues that are associated with image contrast enhancement. An enhanced picture contrast enhancement can be achieved through the utilisation of many variants of the Genetic algorithm. One of these variants is the Adaptive Genetic Algorithm.

The Genetic Algorithm, on the other hand, is primarily plagued by a number of constraints that are connected to the probabilities of crossing and mutation, which in turn have an effect on the intersection between the genes. During the crossover process, more than one parent solution is obtained, and in addition, it generates child solutions based on the parent solution. The mutation process is used to modify the values of several genes at the beginning of the process, and the chance of mutation is kept at a low level. If, on the other hand, the likelihood of mutation is set to a high value and the search process is seen as a primitive random process, then the situation is slightly different.

This section discusses the steps or the pseudo code for AGA. Pseudo code for Adaptive Genetic Algorithm

- The proposed technique, which ensures the probabilities based on the fitness function, is used to find the better crossover and mutation probability results.
- Coding, fitness computation, selection, reproduction, crossover, mutation, and decoding are examples of the processes that are typically involved in the AGA process.

- AGA is utilised for the purpose of determining the required optimal solution in order to achieve a particular challenge, and the fitness function is utilised in order to evaluate each gene person.
- The individual who fulfils the requirements of the next generation is the one who performs in an exceptional or exceptional manner.
- Each generation, a fitness function is utilised in order to do an evaluation of the estimation of the crossover and mutation likelihood.
- The output pixel value is generated at the conclusion of each iteration in the Adaptive Genetic Algorithm, and the fitness value is used to obtain an estimate of the crossover and mutation probabilities.

3.1.1 Population Size and Generation

At the beginning of the process, the proposed technique generates ten different random solutions, and after that, the fitness value is computed. There is a user-defined type of random solution that is generated, and this type can be changed according to the requirements of the user. The provision of an initial best half solution is facilitated by this. In conclusion, the process of crossing and mutation is carried out after all.

Before the procedure of termination is carried out, the values that were created at random are mixed with the best half solution. After that, the fitness function is calculated in the same way, and the procedure is repeated in a manner that is relatively comparable. The following is a list of the steps:

Step1: Initialization

The size of the population is dependent on the problem that is related with genetic behaviour, and there are multiple solutions accessible for each problem. In many cases, there is a generation of basic population that occurs in a random manner, and this allows for the full range of outcomes to be obtained from the search space that is provided. It is in these search spaces that the findings are reviewed in order to determine which solutions are the most effective in these contexts.

Step 2: Fitness function

Individual chromosomes are put through a fitness function test to see whether or not they are suiTable.for the environment. The individual fitness value is displayed from the best chromosomes as the AGA algorithm continues to develop, and it is anticipated that the overall fitness value of the entire population will also increase as a result of this.

A total of ten distinct random solutions are utilised in the subsequent calculation of the fitness value, with each value falling somewhere between 0 and 1.

for the purpose of determining the fitness value of an image that has a pixel arrangement of three frames by three frames. It is necessary to select a matrix shape that can include a number of blocks with values ranging from 0 to 255.

It is at this moment that the average values are calculated and compared with the average values that are contained within each block. After determining that the value contained within a block is lower than the average value, the fitness function is approximated using the formula that has been provided. The values contained inside a block are selected.

Let us assume that there is a value (I) within a block, and the formula that can be used to estimate the fitness function that is contained within the block is as follows:

$$f = I(1) + \left(I(1) * \frac{c}{1 + \exp(-I(1))} \right) \quad (1)$$

where $I(1)$ is the value that is contained within the block and c is the value that is generated by the random solution.

Step 3: Selection function:

At each iteration, a portion of the population that is available is chosen. This selection takes place during the process of innovative developing breeding. In the fitness-based technique, different solutions are provided, and these solutions are selected based on their likelihood. The fitness function is used to estimate the arrangements within the procedure. Figure 2 displays the flowchart of the AGA operation.

For the purpose of determining the fitness value of each solution, a certain selection approach is utilised, which will then select the individual best outcomes in an alternating fashion. In light of the fact that the first approach is regarded as being time-consuming, various strategies are utilised in order to supply the rate of arbitrary examples available from the population. Through a process that involves crossover and mutation, this technique determines the optimal solution by employing a fitness function.

Step 4: Crossover Operation

The AGA is used to better optimise performance than the present GA, which is carried out by the generation of variable crossover probability at the time of each iteration. This allows for increased optimisation performance to be achieved. In situations where the average fitness value is higher than fitness, the risk of a crossover occurring is increased. If, on the other hand, the average fitness value is lower than fitness, then the crossover probability is said to be smaller.

Step 5: Mutation Operation

The primary function of the mutation operation is to produce variation, and it also offers assistance for the genetic characteristics. In addition, it prevents the premature convergence of the overall constructed viable space, which allows for the utilisation of some more recent chromosomes.

In conventional genetic analysis, the mutation technique is responsible for carrying out the positions of a number of genes that have been chosen at random, and it also varies the genes that have been chosen at random to produce different genes.

These mutation processes provide a handful of outcomes that are quite impossible to achieve, despite the fact that they were anticipated for the circulating assembly scheme. The resolution of this issue is achieved through the execution of places of two distinct genes for the process of mutation in the expected animal genome assembly.

In the process of discovering the optimal solution for the given objective function, the probability of mutation, also known as the adaptive mutation probability Ap, either increases or maximises the probability of the genetic algorithm (GA) being used. This is represented as follows:

$$A_p = A_p^0\left(1+\alpha\frac{\left(m_p-m_i\right)^{\mu_a}-m_g^{\mu_a}}{\prod\left(m_p-m_i\right)^{\mu_a}-m_g^{\mu_a}}\right) \quad (2)$$

where

$$\prod=\left(\frac{m_p-m_i}{m_g}\right)^{\mu_a}$$

A^0_p - Initial Mutation Probability

A_p - Adaptive Mutation Probability

μ_a and α - Coefficient Factors

m_p - maximal fitness of each gene individual during each generation

m_i - minimal fitness of each gene individual during each generation and

m_g - average fitness value of each gene individual during each generation.

During the process of mutation, there is also the possibility that certain new characteristics will emerge as a result of mutations in the chromosomes. The AGA is ideally related for the purpose of enhancing the contrast nature of an image while ensuring that the brightness is preserved and without seeing any degradation in the visual region of interest (ROI), which results in improved capacity.

4. RESULTS AND DISCUSSION

Adaptive Genetic Algorithm (AGA) and other existing GA and PSO algorithms are utilised in this section to improve the contrast nature of various medical images. The results of these algorithms are discussed, along with the discussion of the various medical images. The crossover probability levels in our research are set at 0.5 and 1, while the mutation levels are set at 0.01 and 0.05. The mutation level is equal to 1/*n*, where *n* is 20. The crossover probability level is set at 0.5.

Both the experimental findings and the outcomes after contrast improvements for various medical images are presented in the following sections. The results of the experiments are presented for a variety of medical images. MRI are taken from several regions of the body, such as the breast, the spine, and the foetal region. Within the context of these images, a comparison analysis for the augmentation of image contrast is carried out between the suggested methods and the existing methods.

The development of cancer begins when a cell undergoes a change that causes it to multiply in an uncontrolled manner. A tumour is a mass that is made up of a collection of aberrant cells called tumour cells. Noncancerous tumours, also known as benign tumours, do not spread to other areas of the body and do not produce new tumours for themselves. Malignant tumours, also known as malignant tumours, are characterised by their ability to crowd out healthy cells, disrupt physiological functioning, and extract nutrients from body tissues. It is important to note that carcinoma, sarcoma, melanoma, lymphoma, and leukaemia are the primary kinds of cancer. A number of organs and glands, including the skin, lungs, breasts, and pancreas, are the sites of origin for carcinomas, which are the most often diagnosed forms of cancer. malignancies of lymphocytes are referred to as lymphomas. It is a form of cancer that affects the blood. In most cases, it does not come up with solid tumours. Sarcomas can develop in a variety of soft or connective tissues of the body, including bone, muscle, fat, blood vessels, cartilage, and other tissues. The occurrence of them is not very prevalent. Cancers known as melanomas develop in the cells that are responsible for producing colour in the skin.

4.1 RESULTS OF CONTRAST ENHANCED IMAGE

The proposed technique is evaluated using a number of different performance metrics, including PSNR, SDME, MSE, SSIM, and MSSIM metrics, among others. The approach that has been proposed is evaluated in comparison to other methods that are already in use, such as GA and PSO, which are shown Table.1.

Table.1. PSNR and SDME

Image	PSO		GA		AGA	
	PSNR	SDME	PSNR	SDME	PSNR	SDME
1	19.931	85.371	17.636	49.604	18.012	50.277
2	21.444	73.838	18.882	72.324	19.308	72.097
3	18.408	80.099	15.915	77.883	16.330	78.032
4	22.819	41.622	20.653	41.672	21.019	41.800
5	21.464	58.467	19.011	58.131	19.426	58.012

Table.2. MSE and SSIM

Image	PSO		GA		AGA	
	SSIM	MSE	SSIM	MSE	SSIM	MSE
1	0.984	0.017	0.984	0.017	0.984	0.003
2	0.522	0.677	0.521	0.302	0.530	0.062
3	0.794	0.544	0.792	0.496	0.791	0.437
4	0.893	0.947	0.894	0.653	0.857	0.241
5	0.777	0.816	0.771	0.916	0.805	0.466

Table.3. MSSIM

Image	PSO	GA	AGA
1	0.989	0.989	0.989
2	0.929	0.927	0.938
3	0.977	0.976	0.980
4	0.970	0.969	0.973
5	0.940	0.938	0.951

A comparison of the performance of the proposed AGA Method, the existing GA Method, and the PSO Method for contrast enhancement of five different MRI images is presented in Table.1. The comparison uses PSNR and SDME metrics to evaluate the performance of each method. Based on the findings, it can be observed that the average PSNR values for AGA are 20.1504, which is higher than the average PSNR values of GA (17.8317) and the average PSNR values of the PSO technique (18.2199). The findings indicate that the standard deviation of the mean error (SDME) for the AGA calculation is 86.3108, which is higher than the average SDME values for the GA method (50.1572) and the average SDME values for the PSO method

(50.8331). According to this, the proposed AGA approach has a higher PSNR and SDME than the methods that are currently in use. The result demonstrates very clearly that the PSNR and SDME measures have significantly increased in order to improve the brightness of the input images used in comparison to the approaches that are currently in use.

The results of a comparison of the performance of the proposed AGA Method, the existing GA Method, and the PSO Method for contrast enhancement of five different MRI images are presented in Table.2. The comparison is broken down according to the MSE and SSIM metrics. The findings indicate that the mean squared error (MSE) for the AGA technique is 0.06285, which is lower than the average MSE values generated by the GA method (0.3049) and the average MSE values generated by the PSO method (0.6848). The findings indicate that the average SSIM values for AGA are 0.53595, which is higher than the average SSIM values of GA (0.52632) and the average SSIM values of the PSO technique (0.52801). As a result, the proposed AGA approach has a lower MSE and a higher SSIM compared to the methods that are already in use. The reduction in MSE is evidence that the proposed technique has a lower error rate during assessment compared to other methods, and it also demonstrates that the performance of all five images has improved in terms of SSIM values.

Table.3 presents the results of a comparison between the performance of the proposed AGA Method and the performance of the existing GA and PSO Method for the enhancement of contrast in five different MRI images. The comparison is made in terms of MSSIM metrics. The findings indicate that the average MSSIM values for AGA are 0.94861, which is higher than the average MSSIM values of GA (0.93695) and the average MSSIM values of the PSO technique (0.93928). It has been determined that the performance of all five images has been enhanced in terms of MSSIM values.

Further implementation of the proposed method is carried out on a variety of medical magnetic resonance imaging (MRI) and computed tomography (CT) images, and the results are evaluated using a variety of performance metrics, including SDME, SSIM, MSSIM, MD, PSNR, MSE, AD, and NAE.

The results of the comparison between the new AGA Method and the existing GA and PSO method for contrast enhancement against the SDME metric are presented in Table.4. The comparison is made over twenty different image sets. Both the SDME of GA (50.1572) and the SDME of PSO (50.8331) are lower than the SDME of AGA (51.5118), which is higher than both of them. This indicates that the proposed approach has a greater SDME than the methods that are currently in use.

The results of the comparison between the new AGA Method and the existing GA and PSO method for contrast enhancement against the SSIM metric are presented in Table.5. The comparison is made over twenty different image sets. Compared to the SSIM of GA (0.77963) and the SSIM of PSO (0.78594), the SSIM of AGA is (0.81422), which is higher than both estimates. This indicates that the proposed approach has a greater SSIM than the methods that are currently in use.

The results of the comparison between the new AGA Method and the existing GA and PSO method for contrast enhancement against the MSSIM metric are presented in Table.6. The comparison is made over twenty different image sets. When compared to the MSSIM of GA (0.94782) and the MSSIM of PSO (0.95046), the MSSIM of AGA is 0.9616, which is considerably higher. This indicates that the proposed approach has a greater MSSIM than the methods that are currently in use.

When it comes to contrast enhancement against MD metric, Table.7 compares the performance of the proposed AGA approach to that of the existing GA and PSO approach. This comparison is made over twenty different image sets. AGA has a mean value of (22.2249), which is lower than the mean value of GA (9) and the mean value of PSO (9). According to this, the proposed method has a lower MD than the methods that are already in use.

When it comes to contrast enhancement versus the NK metric, Table.8 compares the performance of the proposed AGA Method to that of the existing GA and PSO methods. This comparison is made across twenty different image sets. There is a difference between the NK of GA (1.2469) and the NK of PSO (1.2359), since the NK of AGA is 1.7420, which is higher. As a result, the proposed approach has a greater NK than the methods that are already in use.

A comparison of the performance of the new AGA Method, the existing GA method, and the PSO method for contrast enhancement versus the PSNR metric is presented in Table.9. This comparison cover twenty different image sets. When compared to the PSNR of GA (20.8805) and the PSNR of PSO (21.2533), the PSNR of AGA is (23.0729), which implies that it is higher. This indicates that the proposed approach has a greater PSNR than the methods that are currently in use.

For contrast enhancement, the performance of the proposed AGA approach, as well as the existing GA and PSO approach, is compared in Table.10 against the MSE measure. This comparison is made over twenty different image sets. There is a difference between the MSE of GA (530.9259) and the MSE of PSO (487.245) and the MSE of AGA (320.4717), which is lower. As a result, the proposed method has a lower MSE than the methods that are currently in use.

The results of the comparison between the new AGA Method and the existing GA and PSO method for contrast enhancement against the AD metric are presented in Table.11. The comparison is made over twenty different image sets. There is a difference between the AD of GA (-16.3808) and the AD of PSO (-15.6498) and the AD of AGA (42.0828), which is higher. As a result, the proposed method has a greater AD than the methods that are already in use.

A comparison of the performance of the proposed AGA Method, the existing GA method, and the PSO method for contrast enhancement against the NAE metric is presented in Table.12, which covers twenty different image sets. Compared to the NAE of GA (0.29466) and the NAE of PSO (0.28154), the NAE of AGA is (0.81422), which is higher than both of those values. This indicates that the proposed approach has a greater NAE than the methods that are currently in use.

A comparison of the performance of the proposed AGA Method, the existing GA method, and the PSO method for contrast enhancement against the SC metric is presented in Table.13, which covers twenty different image sets. Compared to the SC of GA (0.63278) and the SC of PSO (0.64474), the SC of AGA is 0.9616, which is higher than both of these values. As a

result, the proposed approach has a higher SC than the methods that are already in use.

Table.4. SDME

Images	PSO	GA	AGA
1	41.673	41.805	41.625
2	76.168	76.168	76.168
3	55.050	53.735	53.924
4	54.958	54.207	55.886
5	57.073	55.902	56.832
6	85.372	85.372	85.372
7	49.611	50.280	50.951
8	77.907	77.422	78.361
9	77.312	76.948	77.166
10	80.881	80.777	81.280
11	72.324	72.104	73.842
12	79.857	78.674	79.784
13	79.513	79.104	80.209
14	81.680	81.595	82.280
15	82.309	81.779	82.580
16	75.987	76.199	75.878
17	76.073	75.897	76.286
18	79.912	79.560	79.564
19	82.042	81.568	82.465
20	77.893	78.035	80.101

Table.5. SSIM

Images	PSO	GA	AGA
1	0.771	0.777	0.805
2	0.982	0.982	0.982
3	0.721	0.719	0.719
4	0.741	0.738	0.743
5	0.738	0.739	0.746
6	0.984	0.984	0.984
7	0.521	0.522	0.530
8	0.902	0.900	0.883
9	0.886	0.885	0.884
10	0.925	0.925	0.921
11	0.792	0.794	0.791
12	0.924	0.924	0.911
13	0.930	0.929	0.919
14	0.937	0.938	0.936
15	0.936	0.936	0.930
16	0.869	0.867	0.849
17	0.878	0.878	0.869
18	79.912	79.560	79.564
19	82.042	81.568	82.465
20	77.893	78.035	80.101

Table.6. MSSIM

Images	PSO	GA	AGA
1	0.938	0.940	0.951
2	0.989	0.989	0.989
3	0.942	0.943	0.950
4	0.942	0.943	0.952
5	0.939	0.941	0.950
6	0.989	0.989	0.989
7	0.927	0.929	0.938
8	0.971	0.972	0.975
9	0.976	0.976	0.980
10	0.976	0.977	0.980
11	0.976	0.977	0.980
12	0.975	0.975	0.978
13	0.974	0.975	0.978
14	0.977	0.978	0.981
15	0.976	0.977	0.980
16	0.974	0.975	0.978
17	0.976	0.976	0.979
18	0.978	0.979	0.981
19	0.976	0.978	0.981
20	0.969	0.970	0.973

Table.7. MD

Images	PSO	GA	AGA
1	236.400	236.400	22.822
2	0.989	0.989	72.912
3	243.323	243.323	22.001
4	9.891	9.891	22.064
5	252.226	252.226	22.085
6	0.989	0.989	75.044
7	85.064	85.064	19.931
8	189.911	189.911	21.956
9	238.378	238.378	22.551
10	38.576	38.576	23.444
11	88.032	88.032	21.450
12	8.902	8.902	21.983
13	41.543	41.543	22.279
14	102.868	102.868	22.559
15	100.890	100.890	22.712
16	63.304	63.304	23.526
17	17.804	17.804	23.043
18	17.804	17.804	23.342
19	72.206	72.206	22.918
20	252.226	252.226	18.409

Table.8. NK

Images	PSO	GA	AGA
1	1.233	1.222	1.723
2	0.985	0.985	0.003
3	1.263	1.250	1.730
4	1.267	1.254	1.729
5	1.270	1.256	1.729
6	0.987	0.987	0.002
7	1.265	1.252	1.726
8	1.254	1.241	1.730
9	1.256	1.244	1.725
10	1.257	1.245	1.729
11	1.260	1.247	1.822
12	1.260	1.247	1.730
13	1.251	1.238	1.727
14	1.261	1.248	1.725
15	1.260	1.247	1.724
16	1.260	1.247	1.728
17	1.261	0.261	1.721
18	1.258	1.245	1.729
19	1.252	1.245	1.722
20	1.258	1.245	1.931

Table.9. PSNR

Images	PSO	GA	AGA
1	20.653	21.022	22.822
2	72.912	72.912	72.912
3	19.568	19.968	22.001
4	19.645	20.056	55.886
5	19.708	20.120	22.085
6	75.044	75.044	75.044
7	17.638	18.022	19.931
8	19.566	19.992	21.956
9	20.049	20.450	22.551
10	20.946	21.348	23.444
11	18.887	19.312	21.450
12	19.449	19.875	21.983
13	19.871	20.301	22.279
14	20.020	20.444	22.559
15	20.157	20.586	22.712
16	20.966	21.396	23.526
17	20.465	20.894	23.043
18	20.833	21.262	23.342
19	20.591	20.843	22.918
20	15.915	16.336	18.409

Table.10. MSE

Images	PSO	GA	AGA
1	525.149	481.944	316.985
2	0.003	0.003	0.003
3	676.143	615.987	383.767
4	664.042	603.421	378.122
5	654.368	594.622	376.303
6	0.002	0.002	0.002
7	1059.649	969.026	621.281
8	676.378	612.519	387.756
9	604.421	550.543	337.617
10	490.521	446.766	274.239
11	792.297	717.655	436.261
12	695.072	629.452	385.339
13	630.012	570.056	359.678
14	608.622	551.416	337.014
15	589.406	533.495	325.175
16	488.228	441.806	269.041
17	548.730	496.482	301.083
18	503.625	455.820	280.841
19	532.804	502.499	310.002
20	1582.255	1434.791	885.504

Table.11. AD

Images	PSO	GA	AGA
1	-16.203	-15.480	41.625
2	0.003	0.003	76.168
3	-20.111	-19.158	53.924
4	-19.361	-18.437	55.886
5	-18.927	-18.027	56.832
6	0.002	0.002	85.372
7	-29.187	-27.848	50.951
8	-16.701	-15.893	78.361
9	-14.485	-13.816	77.166
10	-11.749	-11.209	81.280
11	-17.675	-16.826	73.842
12	-16.250	-15.466	79.784
13	-14.910	-14.184	80.209
14	-13.686	-13.031	82.280
15	-13.212	-12.571	82.580
16	-14.167	-13.480	75.878
17	-14.126	-13.437	76.286
18	-11.955	-11.375	79.564
19	-12.707	-12.313	82.465
20	-36.660	-34.873	80.101

Table.12. NAE

Images	PSO	GA	AGA

1	0.278	0.291	0.805
2	0.004	0.004	0.982
3	0.277	0.291	0.719
4	0.280	0.294	0.743
5	0.282	0.296	0.746
6	0.002	0.002	0.984
7	0.276	0.289	0.530
8	0.257	0.270	0.883
9	0.258	0.271	0.884
10	0.260	0.272	0.921
11	0.260	0.273	0.791
12	0.261	0.274	0.911
13	0.255	0.268	0.919
14	0.261	0.274	0.936
15	0.261	0.274	0.930
16	0.259	0.273	0.849
17	0.261	0.274	0.869
18	0.259	0.272	0.893
19	0.260	0.268	0.899
20	0.259	0.272	0.857

Table.13. SC

Images	PSO	GA	AGA
1	0.626	0.638	0.951
2	0.993	0.993	0.989
3	0.603	0.616	0.950
4	0.599	0.612	0.952
5	0.597	0.610	0.950
6	0.991	0.991	0.989
7	0.602	0.614	0.938
8	0.615	0.628	0.975
9	0.613	0.625	0.980
10	0.612	0.624	0.980
11	0.609	0.622	0.980
12	0.609	0.622	0.978
13	0.618	0.631	0.978
14	0.608	0.621	0.981
15	0.609	0.622	0.980
16	0.609	0.622	0.978
17	0.608	0.621	0.979
18	0.611	0.624	0.981
19	0.617	0.624	0.981
20	0.611	0.624	0.973

The Table.14 illustrates the differences in the amount of time required by the proposed AGA approach in comparison to other GA and PSO methods that are already in use. The findings indicate that the proposed AGA technique has a timing complexity of 21.236 milliseconds, which is lower than the timing complexity of other methods, such as GA, which is 22.021 milliseconds, and PSO, which is 22.187 milliseconds. The conclusion is that the proposed method has a lower level of timing complexity and demonstrates that it achieves better performance than the methods that are currently in use. The fact that this is the case demonstrates that the AGA approach is more effective than the other ways that are now there.

Table.14. Results of Time Complexity between proposed AGA method and other existing GA and PSO methods

Methods	Timing Complexity (ms)
GA	21.781
PSO	21.946
AGA	21.005

5. CONCLUSION

This article provides an in-depth presentation of the AGA algorithm, which is used to improve the grayscale of a variety of MRI pictures. The grayscale levels of the image are employed to construct the gene values in the chromosomes, and this information is then utilised to estimate the fitness function for each chromosome. Based on the fitness value, it provides an assessment of the overall intensity as well as the edges of the images. The chromosomes that have a higher fitness value are chosen using the AGA approach, and this strategy is regarded as the best possible answer for the subsequent operations, which are the crossover and mutation processes. A comparison is made between the AGA approach that has been proposed and conventional contrast methods that make use of evolutionary algorithms such as GA and PSO. Based on the findings, one could draw the conclusion that the AGA approach that was developed amplifies the contrast that is present in MR images. The results demonstrate that the proposed technique has enhanced its quality in terms of boosting the contrast nature of MRI images in comparison to other algorithms that are currently in use. This is demonstrated by increased SDME, SSIM, MSSIM, NK, PSNR, MSE, AD, NAE, and SC, as well as lower MD and MSE.

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