Applications Research of Improved Genetic Algorithm in Image Denoising

Ming Chen

1College of Computer and Information Technology, China Three Gorges University, Yichang, China

Abstract: In the process of generation, transmission and recording, image signals are often disturbed by various noises, which seriously affect the visual effect of images. Noise is the main factor affecting image quality, which has a great influence on the subsequent processing of images. Therefore, it is of great practical significance to adopt appropriate methods to reduce noise. In this paper, several common methods of image noise removal are introduced, and the denoising quality evaluation model is given. The traditional genetic algorithm has the characteristics of slow convergence and big relevant error in image denoising. We improved the genetic algorithm and applied it into image denoising. Experimental results show that the improved genetic algorithm has faster convergence speed and smaller relative error, which improves the efficiency and quality of image denoising.

1. Introduction

When the image noise is serious, the image is almost distorted, which makes the image lose the essential meaning of storing information. Obviously, image denoising is a necessary guarantee for correct identification of image information. In addition to improving the accuracy of human visual recognition information, the significance of image denoising lies in that it is a reliable guarantee for further processing of images. If an image containing noise is processed with feature extraction, registration or image fusion, the results are certainly not satisfactory, so image denoising is necessary. In the field of digital image processing, there are many traditional methods of image denoising. They may have been put forward and used for a long time. In this academic background, the significance of image denoising is that in the field of image denoising, the traditional denoising methods are in full bloom, but these methods are not perfect, mainly in the denoising and the loss of the edges and details of the image. Therefore, further research on new denoising methods or improvement of existing algorithms is still of great significance. Different algorithms have different mathematical theories, and the effect of image denoising is different. It is also meaningful to explore the internal mechanism of them, to find the corresponding relationship and to study how to make up the short of different algorithms to achieve better denoising effect. Research on image denoising is also helpful to improve the performance of other digital image processing links.

The conventional image denoising method will cause blurring of the image edge, while preserving and enhancing the edge of the image, it will also affect the image denoising effect. Therefore, finding a filtering algorithm that can remove noise and preserve image edges and other features has always been a key issue in this field. With the continuous maturity and perfection of various theories, digital filtering technology has made great progress and has been widely used in many fields, such as medicine, remote sensing, infrared and so on. Now many universities and scientific research institutions both at home and abroad have special machine vision laboratories to carry out more in-depth research on this technology.
It is believed that with the continuous deepening of this research, better methods will be put forward and applied to the rapid development of image processing technology, and image segmentation is also a graph. Like the foundation of processing technology. Edge detection and denoising is an important technology in image segmentation. Image denoising can improve image quality. Edge contour carries many information. Therefore, image denoising and image edge extraction provide an important guarantee for accurate analysis of image information and accurate segmentation.

2. Image noise and evaluation methods of denoising quality

2.1. Image noise

Noise in an image can be defined as an undesirable part of the image or an unwanted part of the image. Noise may have some randomness, such as salt and pepper noise on screen, and it may be more regular or regular. Therefore, noise has both stochastic and regular characteristics. The actual image is generally noisy because of some interference. The cause of noise: the internal noise caused by the mechanical vibration of some parts of the electrical apparatus caused by the random motion of the load particle, the noise produced by the change of the electric current or the change of the electromagnetic field; the external natural magnetic pads or power lines introduce the external noise produced by the internal system. Noise from particles of photographic material or defects on magnetic tape disk surface, interference of transmission channel, quantization noise, decoding error noise and so on. The cause of noise determines the distribution characteristics of noise and its relationship with image signals. Because the image is affected by the ingestion device and the surrounding environment during the intake process, the image contains noise, and the noise is usually produced randomly, so it has the irregularity of distribution and size. Some noise and image signals are independent and irrelevant, some are related, and the noise itself may be related. Generally, there are some common noises in image processing technology: additive noise. It is not related to the intensity of the image signal, such as the channel noise introduced by the image in the transmission process, the noise of the camera scanning the image, etc. Multiplicative noise. It is related to image signal and varies with the change of image signal. Such as flying point scanning image noise, television scanning grating, film particle noise. Quantization noise. The quantization noise is the main noise source of the digital image, and its size shows the difference between the digital image and the original image. The best way to reduce the noise is to choose the optimal quantized measure according to the probability density function of the level.

2.2. Common methods of image denoising

Since the 1970s, scholars have proposed many algorithms for image denoising. These algorithms are based on the actual characteristics of digital images and the distribution pattern of image noise. The traditional digital image denoising algorithms can be roughly divided into two categories: spatial domain filtering algorithm and frequency domain filtering algorithm. The algorithm in the spatial domain means that the value of the pixels of a digital image is processed directly by a specific method. The traditional mean filtering, median filtering, bilateral filtering and Gauss function filtering are all using this algorithm. At present, more novel algorithms based on probability statistics and partial differential equations are also spatial domain algorithms. The spatial domain denoising is divided into local digital image denoising and non-local image denoising.

The local denoising methods in space domain include Gauss function filtering, mean filtering and so on. This method uses the adjacent pixels in the natural digital image to be connected to each other and composing the characteristics of the digital image structure together. It is considered that the current pixel value of the digital image is only closely related to the pixels adjacent to the geometric distance. The core idea of this method is to estimate the true value of the current digital image pixels by using the pixel value of the digital image in the geometric neighbourhood. In different ways, the weights of pixels in different neighbourhoods are different. The denoising method of Gauss function filtering: the weight of the domain pixels in the digital image is determined by the Gauss function of its distance from the central pixel. The smaller the distance from the centre pixel, the greater the weight of the pixel, the
greater the weight of the pixel, the estimation method of the mean filtering: all the digital image pixels around the image pixels around the current digital image. The weight of the neighbourhood pixels is regarded as the estimated value of the pixel of the current digital image. The estimation method of the bilateral filtering: to improve the filtering method of the Gauss function, the weight of the neighbourhood pixels is not only related to the distance, but also is related to the similarity of the value between the pixels of the digital image, that is, with the current pixel. The closer the distance and the more similar the value, the greater the weight of the digital image pixels.

Median filtering is a nonlinear signal processing technology which can effectively suppress noise based on the sorting statistics theory. In the year of time series analysis, the concept of median filter was proposed, and later it was introduced into image processing. This filter has the advantage of simple operation and fast speed. It shows excellent performance in filtering superposed white noise and long tail noise. Median filter can filter out noise, especially impulse noise, and protect signal details such as edge, acute angle, etc. In addition, the median filter is easy to self-adapt, which can further improve its filtering performance. Therefore, it is very suitable for digital image processing applications where some linear filters are incompetent. Median filtering is a commonly used nonlinear smoothing filter. It is a neighbourhood operation, like convolution, but not weighted sum calculation. The main principles are: first determine a neighbourhood of a pixel as the centre, generally a square neighbourhood, and then sort the values of each pixel in the neighbourhood and take the middle value as the new value of the centre pixel level, and the neighbourhood is usually called the window. Median filtering is moving along an image with an active window, and the pixel level is replaced by the median of all the pixels in the window.

2.3. Evaluation methods of denoising quality

After image denoising, how to evaluate image quality is particularly important. The evaluation methods include subjective evaluation method, fidelity criterion or distortion criterion, the objective standard measurement method and the new quality evaluation method. With the development of image processing technology, the new quality evaluation method is a new research trend of the image evaluation method. It develops from the former simple error statistics method to the error statistics method that combines the visual characteristics of human eyes. Its current research results are divided into two categories: visual perception and visual interest. The simple method in the subjective evaluation method is that the observer organizes a group of people to evaluate the image denoising effect with the naked eye. After the observation, the image denoising effect is evaluated by the comprehensive owner. The result is related to the two factors: the first factor is related to the observer itself and the environment of the observation; the second factors are the same. The nature of the image itself is related. Because the result of the image is still accepted by human vision, subjective evaluation method has become one of the most commonly used methods in the field of image denoising.

To overcome the disadvantages of simple local averages, many local smoothing algorithms preserving edge details have been proposed. The focus of their discussion is on how to choose the size, shape and direction of the field, how to choose the number of points to participate in, and the weight coefficient of the neighbourhood points. If the noise interfered image is seen in a two-dimensional random field, the statistical theory can be used to analyse the signal to noise ratio of the noisy image. In general, the noise is additive noise, and the mean value of the independent Gauss white noise is zero and the variance is occupied. We define the signal-to-noise ratio as a noisy image. The ratio of the mean to the noise variance is that the signal to noise ratio will increase tens of thousands of times as the number of pixels in the domain. The larger the neighbourhood, the more pixels, the more the signal to noise ratio, the better the smoothness. To further measure the performance of this improved threshold, we choose MSE and PSNR to analyse the effect of denoising. The smaller the MSE value and the larger the PSNR value, the better the image quality after denoising. The definitions are:

\[
MSE = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (g_{jk} - f_{jk})^2
\]
Among them, M×N is the image size; \( g_{jk} \) is the image with no noise and \( f_{jk} \) is the image after denoising.

Through the analysis of the subjective evaluation method and the objective standard measurement method, it is found that each of them has its own characteristics. Although the subjective evaluation method cannot make quantitative analysis of the image quality, it can give play to the human visual characteristics; the objective standard measure is a quantitative description of the image quality, and the disadvantage is that it cannot reflect the subjective of the human being. To sum up, the simple method of visual observation in the subjective evaluation method, the methods of MSE and PSNR in the objective measurement method are combined to measure the denoising effect of the image.

3. Concept and process of genetic algorithm

3.1. Concept of genetic algorithm

All living things in the world are inherited from their parents, and this life phenomenon is called heredity. Genetic algorithm is a global optimization random probability search algorithm, which is first proposed by J.H.Holland of Michigan University in the United States by using the evolutionary process of the population in the natural world to simulate the genetic and variation of the chromosomes in the population.

Genetic algorithm is a highly parallel global probability search algorithm, which simulates the genetic and evolutionary process of the population in nature. It embodies the natural law of "the survival of the fittest, the survival of the fittest". The genetic algorithm runs high efficiency, can handle problems in parallel and searches from the global point of view. It can learn and accumulate the knowledge of its space actively in the search and reduce the search scope to achieve the optimal solution. The genetic algorithm maps the problem to the natural environment of the population. Every potential solution of the problem represents an individual in the population. Then the set of all the potential solutions of the problem constitutes a population, and the fitness of everyone is calculated based on the fitness function to measure the adaptability of the individual to the environment. In the algorithm operation, starting from the random initial population, in the process of population evolution, according to the individual fitness value of everyone, a new population with more ability to survive in the environment is generated by the operation of three genetic operators of selection, cross and mutation, and the population search space is gradually reduced to the better areas. With the iteration of the algorithm, the fitness value of the population will be improved continuously. Finally, it converges to the individual with the highest environmental adaptability and the strongest survivability and obtains the optimal solution of the problem. Before solving the genetic algorithm, we need to encode the problem first and generate the initial population randomly according to the coding. The algorithm starts from the initial population and generates new species by genetic operators.

3.2. Process of genetic algorithm

In general, the genetic algorithm cannot directly deal with the solution space of the problem and must be converted into a search space which the algorithm can handle according to some rules. This is the coding. The spatial encoding of the problem solution is the first step of the genetic algorithm. The population generated by coding can be manipulate by genetic operators. The selection and design of the coding rules are very important for the performance of genetic algorithms. It determines the decoding method of the genetic space to the solution space and has a great influence on the efficiency of the genetic operator. Binary encoding, symbol encoding and floating-point coding are commonly used encoding rules. In binary encoding, the gene value is \{0,1\}, and everyone is a long string composed of characters 0 and 1 in a specific order. According to schema theory, almost all problems can be represented by binary encoding. Therefore, binary encoding has become the most commonly used coding scheme in genetic algorithm. Binary coding is simple, but the length of chromosomes will
increase rapidly when the number of optimized parameters is increased by binary coded individuals, which leads to a large increase in the computational complexity of genetic operators and a significant decrease in computational efficiency. At this point, floating-point number coding is the first choice. In floating point coding, each gene value of a floating point is a floating-point number, and the true value of the parameter to be optimized is generally used. This method can not only shorten the length of chromosomes, but also reduce the workload of the conversion computation and improve the efficiency of the algorithm. Symbol coding means that the gene positions of individual chromosomes are symbols with code meaning and have no specific numerical significance. This method fits the principle of block coding, and many professional knowledges can be applied in the algorithm, but it is not convenient for genetic operators to select, cross and variation the individual. The process of genetic algorithm is shown in Figure 1.

![Figure 1. Process of genetic algorithm](image)

4. Image denoising method based on improved genetic algorithm

4.1. Improvement direction

Compared with other optimization algorithms, the advantage of genetic algorithm is that its solution to the target problem is entirely dependent on the individual and its fitness in the solution space, without other additional conditions, so it has a strong solution ability for solving complex nonlinear and non-structural problems, but it uses traditional heredity. When selecting the optimal edge detection threshold,
there are some defects such as slow convergence rate or premature convergence, which makes the difference between the optimization result and the optimal solution. Therefore, the traditional genetic algorithm is improved in this section. The improved genetic algorithm not only improves the convergence speed of the algorithm, but also gets the optimal results very close to the optimal solution. The main idea of this improved genetic algorithm is to find the global optimal solution in two times, that is to use the results of the first search to determine the selection range of the initial population of the second optimization, because the first optimization may not necessarily be the global optimal solution, but it must be a better result, so I will be a better result. We can limit the initial population of the second optimization process to a neighbourhood of the first search result. Currently, the fitness of the second initial population is higher. According to the genetic theory, the two genes are excellent individuals, and their offspring are more likely to be superior than those of two individuals in general, so in theory, this algorithm is feasible and is more conducive to the search for global optimal solutions.

4.2. Basic flows of improved genetic algorithm in image denoising
If the image is a level grayscale image, the value of the image is encoded by eight-bit binary encoding. First, an individual is generated randomly at the same probability as the initial population of the first optimization. The step is to select a cross-operated individual by rotating the wheel, and select two individuals each time, so that a new population can be selected according to the probability of proportional to the fitness value. The practice is to calculate and sum up the fitness value of everyone in the initial group, and remember it as a number, and then add it from the first individual until the cumulative value is greater than the random number, and the last accumulative individual is the individual to be selected. This method is used to select two individuals according to a certain crossover probability. Random selection starts at one point and crosses operation to generate two new individuals. So repeat, until the generation of a new generation of groups select a thousand individuals according to a certain probability of mutation, and then randomly select a certain location for a mutation operation to form a new group meaning. To prevent the mutation operation to destroy the highest solution of the last generation group, we use the first one. The individuals with the highest fitness in the generation group compare with the individuals with the lowest fitness in the group. If the former is more adaptable than the latter, the former is replaced by the former, otherwise it will not be replaced. The purpose of this approach is to prevent the degradation of population and lead to slow convergence, which can significantly speed up convergence. After this step, the final generation of the group will be formed. If the stop condition is satisfied, if the new group is not satisfied, move the new group as a person, otherwise, go to the next step for the second time. In this step, the first optimization of the first population is the centre of the initial population, which generates the initial population of the initial population with the same probability and generates the initial population of second optimization by the same probability as the second optimization. The steps are repeated step by step until the final group satisfying the stopping condition is finally generated. The procedure compares the most adaptable individual with the first optimization in the final generation of second optimized groups. If the former is large, the former is the final threshold, otherwise the latter is retained as the final threshold. This is because it is possible that the result of the first optimization is close to the optimal solution, but the result of the second optimization converges to a less good value.

4.3. Experiment results of improved genetic algorithm in image denoising
The improved genetic algorithm is used to analyse the threshold of the image with high frequency reconstruction edge image: the image is 256 level level image, so bit binary coding is used. The number of initial population is 10. According to the test selection, the cross rate is 0.9 and the mutation rate is 0.2. The termination condition is that the algorithm stops when the maximum number of iterations is set and the average fitness of the new population is between the average fitness of the previous generation and the ratio of 1.0-1.05. The initial population of the second optimization is generated in the neighbourhood of the radius of the first optimization result, that is, $A=50$. The results show that the improved genetic algorithm in image denoising has a good performance in image denoising.
Table 1. Experiment data contrast of genetic algorithm and improved genetic algorithm

| Experiment time | Iteration times of genetic algorithm | Relative error of genetic algorithm | Iteration times of improved genetic algorithm | Relative error of improved genetic algorithm |
|-----------------|--------------------------------------|------------------------------------|-----------------------------------------------|---------------------------------------------|
| 1               | 6                                    | 0.05                               | 5                                            | 0.02                                        |
| 2               | 7                                    | 0.09                               | 3                                            | 0.05                                        |
| 3               | 9                                    | 0.12                               | 3                                            | 0.09                                        |
| 4               | 12                                   | 0.03                               | 9                                            | 0.09                                        |
| 5               | 12                                   | 0.21                               | 9                                            | 0.11                                        |
| 6               | 4                                    | 0.2                                | 1                                            | 0.05                                        |
| 7               | 7                                    | 0.05                               | 6                                            | 0.01                                        |
| 8               | 5                                    | 0.15                               | 3                                            | 0.12                                        |
| 9               | 4                                    | 0.16                               | 2                                            | 0.04                                        |
| 10              | 8                                    | 0.09                               | 5                                            | 0.05                                        |

5. Conclusions

Based on introducing the theory of image denoising, this paper mainly improves the denoising method of genetic algorithm. The main conclusions are as follows:

(1) This paper systematically introduces traditional image denoising technologies and gives the evaluation method of image denoising quality.

(2) The concept and process of genetic algorithm are given in this paper. It is pointed out that the genetic algorithm has the features of slow convergence speed and large relative error of in image denoising.

(3) The basic process of image denoising based on improved genetic algorithm is presented in this paper. Practice has proved that the improved genetic algorithm is superior to the traditional genetic algorithm in terms of convergence speed and relative error.

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