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Improved Canny edge detection algorithm based on deep learning

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Abstract

In the edge detection algorithm, effectively reducing the noise in the image is the key to edge extraction. In order to solve the problem that the traditional Canny operator needs to set the variance and high and low threshold artificially, the particle swarm optimization algorithm in deep learning is proposed to adaptively optimize the Gaussian filter. The advantages of the proposed method are verified by comparing with the traditional Canny algorithm. The experimental results show that the improved algorithm has better adaptability, can suppress the noise well, reduce the false detection rate, and the detected image contour is clearer.

Keywords

Canny; edge extraction; adaptive; particle swarm optimization algorithm.

1. Introduction

As an important research direction in image processing technology[1], edge detection technology can simulate human visual structure and obtain image edge information. This technology mainly extracts the image edge feature points of the detected object, which has the advantages of good anti noise performance and accurate positioning. This technology is widely used in license plate recognition, iris recognition, face detection, trademark image retrieval and other fields [2].

The core of edge detection technology is how to reduce the noise and improve the accuracy of edge extraction. The key is to select the appropriate noise reduction algorithm for image denoising. Therefore, it is a very important research topic to study the new filtering algorithm and effectively enhance the image edge, which can effectively filter the noise and ensure the edge detection The results of the measurement are satisfactory. Canny algorithm is not easy to be interfered by noise, and has good denoising ability and high detection accuracy. It can accurately locate the image edge, and the effect of edge detection is good. However, Canny algorithm needs to set parameters artificially, which is affected by Gaussian noise. The detection effect of Canny algorithm in salt and pepper noise environment is not ideal, and the discontinuities of image edge are easily mistaken for noise and ignored, which leads to the poor effect of edge detection. In recent years, many scholars have improved Canny algorithm. In reference [3], an improved median filter with window size of is proposed to replace Gaussian filter for smoothing. Although this method reduces the amount of computation, it has poor adaptability and filtering effect under different degrees of salt and pepper noise. Reference [4,5] proposed to use adaptive median filter instead of Gaussian filter. This method has a good adaptive effect on salt and pepper noise, but it has a large amount of computation and a poor denoising effect on Gaussian noise. In reference [6], OTUs algorithm is introduced to calculate

high and low thresholds according to the distribution of pixel gradient values, which increases the adaptability of the algorithm. However, the traditional Otsu algorithm needs to traverse each pixel gradient level to determine the maximum inter class variance value, which is inefficient.

In view of the above problems, this paper introduces particle swarm optimization algorithm to optimize the key parameters of Gaussian filtering algorithm from the perspective of improving the effect of noise reduction, and finally realizes the image edge extraction. Compared with the traditional Canny edge detection algorithm based on Gaussian filter, this algorithm has the advantages of high signal-to-noise ratio and accurate positioning, which can make the image edge detection achieve ideal accuracy.

2. Canny principle and improvement

2.1. Canny algorithm principle description and defect analysis

Canny edge detection algorithm [7] is a classical edge detection algorithm developed by John F. canny in 1986. The basic idea is to use two-dimensional Gaussian function as noise filter, convolute with the image, and then use the filtered image to find the maximum local gradient, and find the image edge according to the maximum local gradient. The algorithm steps are as follows [8]:

(1) Gaussian filter smoothes the image.

(2) The differential operator is used to obtain the partial derivative and calculate the gradient amplitude direction of the image.

(3) According to the gradient direction, the gradient amplitude is suppressed by non maximum value, and the point with the maximum local gradient value is retained.

(4) Double threshold algorithm is used to detect and connect edges.

Canny operator uses Gaussian filter for image denoising, and its function is as follows:

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}) \tag{1}$$

$$E_x=\frac{\partial G(x,y)}{\partial x}*f(x,y) \tag{2}$$

$$E_y=\frac{\partial G(x,y)}{\partial y}*f(x,y) \tag{3}$$

Among, $G(x,y)$ Represents a two-dimensional Gaussian function, E_x, E_y Represents the filtered image,$f(x,y)$ Represents the original gray image.* Represents convolution, σ Determines the smoothness of the image. In the filtering process σ and T_1, T_2 All three parameters need to be set manually [9]. Due to the contradiction between continuous edge and false edge, Gaussian filtering is difficult to achieve a balance between filtering noise and maintaining image edge [10]. If the value of the parameter is too small, the noise can not be effectively filtered, resulting in poor filtering effect. If the value is too large, the filtering effect can be enhanced, but the strong edge information will be smoothed, leading to the missing edge detection. At the same time, fixed parameters can not make every image achieve the optimal effect when processing different images. Therefore, particle swarm optimization algorithm is proposed to optimize the noise reduction parameters of Gaussian filter before edge extraction, which can ensure the quality of the extracted image and avoid the selection of Gaussian parameters in Canny algorithm.

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2.2. Description of particle swarm optimization

Particle swarm optimization (PSO) algorithm [11] is a stochastic optimization technology based on population, which was proposed by Kennedy and Eberhart in 1995. The main idea of PSO algorithm is evolutionary algorithm and group pattern, so that it can search a large range of optimization objective function solution space at the same time [12].

Variance can reflect the deviation degree of the gray value of the image to a certain extent. Because it is vulnerable to noise and other interference, it will lead to index distortion. Variance is defined as[13]:

$$\sigma^2 = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[f(i,j) - \overline{f} \right]^2 \tag{4}$$

Among, $\overline{f}$ It is the mean value of the image. According to the analysis of formula 4, it can be seen that the variance is used to measure the image clarity. Therefore, the method of finding the optimal average gradient value can be used to optimize the parameters in the noise reduction algorithm:

(1) According to the evaluation of noise reduction effect, the reasonable parameter range is selected.

(2) Initialize the parameters of PSO.

(3) According to the energy value of adjacent pixels, the noise reduction function is constructed and processed;

(4) The denoised data is reconstructed to obtain the denoised image information.

(5) The variance between the denoised image and the denoised image is calculated as the fitness value of particle swarm optimization algorithm to obtain the initial minimum fitness value.

(6) The parameters are updated locally and globally by cyclic iteration, and the constant coherence function between the denoised image and the denoised noise is calculated as the current fitness value;

(7) Compare the current fitness value and the minimum fitness value, if the current fitness value fit is less than the minimum fitness value min_ Fit, the current fitness value s is updated to the minimum fitness value a, and the corresponding parameters are saved, otherwise the minimum fitness value and parameters remain unchanged.

(8) The iteration cycle is continued, and steps (6) and (7) are repeated to further implement local parameter optimization and global parameter optimization to update the fitness value and parameters until the set number of iterations is completed;

(9) The global minimum fitness value and global optimal parameters are obtained by updating.

3. Experiment and result analysis

3.1. Analysis of optimization results

In the optimal population obtained by particle swarm optimization, the fitness values corresponding to different parameters and the PSNR results after noise reduction are shown in Figure 2. It is not difficult to see from the analysis of Figure 2 that with the increase of the number of iterations, the PSNR value reflecting the noise reduction effect gradually increases, and the noise reduction ability is enhanced. At the same time, from the change trend of PSNR value, it can be seen that it is correct to take the variance value between the data before and after noise reduction as the indirect evaluation index of noise reduction effect. In the noise reduction processing of non simulation data, this evaluation method can replace the PSNR value in the noise reduction analysis of simulation signal as the evaluation basis of noise reduction effect.

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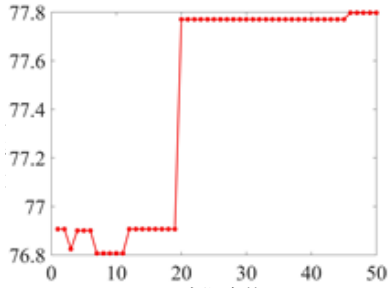

Fig. 1 Noise reduction effect of different parameter values

3.2. Contrast experiment of edge detection

In order to verify the advantages of the improved Canny edge extraction method in edge extraction, we add 0.01 and 0.02 salt and pepper noise to the image respectively. The improved Canny edge extraction method is compared with the traditional Canny algorithm and the traditional Canny algorithm. The experimental results are shown in the figure below.

(a) with 0.01 salt and pepper noise (b) Traditional Canny (c) Improve canny

(a) with 0.02 salt and pepper noise (b) Traditional Canny (c) Improve canny

Fig. 2 Experimental results of salt and pepper noise

It can be concluded from Figure that the improved Canny edge extraction method can effectively remove the image noise through the preprocessing of image noise reduction, and the extracted edge information is accurate and clear. Due to the influence of the noise in the image, the traditional canny method leads to the error of edge information detection, a large number of non effective edge information is extracted, which affects the accuracy of the original image edge information. However, the improved Canny edge extraction method can extract the edge information relatively effectively, and there is basically no noise component interference and incorporation.

Table 1 Comparison of PSNR value (DB) of salt and pepper noise

Algorithm type	0.01 salt and pepper noise	0.05 salt and pepper noise	0.1 salt and pepper noise
Traditional Canny	62.5702	55.9509	54.3435
Improve canny	64.6721	58.2438	55.8440

As shown in Table 1, the peak signal-to-noise ratio results of the two algorithms in dealing with different degrees of salt and pepper noise. From the data in Table 1, it can be concluded that the PSNR of the improved algorithm is increased by about 2 dB compared with that before the improvement, which can more effectively suppress the noise.

4. Summary

In this paper, aiming at the problems of traditional Canny operator, an improved edge detection algorithm is proposed. On the basis of traditional Gaussian filter, particle swarm optimization algorithm is used to optimize the characteristic parameters. This algorithm can make up for the shortcomings of Gaussian filter in noise reduction, which requires artificial setting of parameters, and for salt and pepper noise, the noise reduction effect is not obvious. The experimental results show that when there is salt and pepper noise, the PSNR value of the improved algorithm is increased by about 2 dB compared with that before the improvement. The improved algorithm retains more image edge details, and the extracted lines are clearer, which can generate higher quality edge images.

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