Research Article

Image Edge Detection Algorithm Based on Fuzzy Radial Basis Neural Network

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Digital image processing technology is widely used in production and life, and digital images play a pivotal role in the ever-changing technological development. Noise can affect the expression of image information. The edge is the reflection of the main structure and contour of the image, and it is also the direct interpretation of image understanding and the basis for further segmentation and recognition. Therefore, suppressing noise and improving the accuracy of edge detection are important aspects of image processing. To address these issues, this paper presents a new detection algorithm combined with information fusion based on the existing image edge detection techniques, and the algorithm is studied from two aspects of fuzzy radial basis fusion discrimination, in terms of preprocessing algorithm, comparing the denoising effect of mean and median filters with different template sizes on paper images with added noise, and selecting the improved median filter denoising, comparing different operator edge detection. The effect of image edge detection contour is finally selected as the $3 * 3$ Sobel operator for edge detection; the binarized image edge detection contour information is found as the minimum outer rectangle and labeled, and then, the original paper image is scanned line by line to segment the target image edge region. The image edge detection algorithm based on fuzzy radial basis fuser can not only speed up the image preprocessing, meet the real-time detection, and reduce the amount of data processed by the upper computer but also can accurately identify five image edge problems including folds and cracks, which has good application prospects.

1. Introduction

With the continuous development of network technology in today's society, the role of information acquisition, storage, and transmission in the development of human society is particularly prominent. The development of image information technology plays a pivotal role in people's lives. As the collection of image information becomes more and more comprehensive, the requirements for image quality are gradually improving. At present, image processing has been applied to many aspects of life [1]. It has played an important role both in military and civilian fields, such as criminal investigation in the public security department, target capture in the radar system, and inspecting in the medical equipment. In this paper, we study the denoising and edge detection in image processing and propose the improvement of the method and the joint application of the processing

method based on the theory of fuzzy radial basis neural network. In the process of acquisition and transmission of images of external terrain and landscape [2], there will inevitably be external noise, as well as the system noise of the sensor itself, so the image will be superimposed with more noise during the imaging process causing degradation of image quality. Image noise seriously affects people's visual judgment and analysis and thus loses some useful information. Therefore, image processing is required after image acquisition and transmission. And noise cancellation is an essential part of it. Traditional denoising means denoise the image by filters and the corresponding median filter, low-pass and high-pass filter, mean filter, etc., but the traditional filter is processed after image denoising. Phenomena such as blurring and distortion of the image often occur, so the denoising method needs to be improved [3]. The integrity of edge information is a prerequisite for the

extraction of useful information for an image. Edges are also the most basic features of an image. Edge information is also an evaluation of the quality of the image, and the edge is used to judge and detect sudden changes in the gray value of the image. Different spectral gray values are not the same, but they can be extracted from their common point with edge detection, from the perspective of remote sensing images. The detection technology can extract the complete remote sensing image edge, and it has become an important means of image processing. However, some classical edge detection algorithms are sensitive to noise and will mistakenly detect noise as edges in the processing [4]. Therefore, edge detection needs to be improved. Image denoising and image edge detection are not only the prelude to image processing and recognition but also have important significance for image postprocessing: image denoising is to remove the excess noise to make the image quality and visual effect better, while image denoising is the basis of image matching and segmentation and is an important processing premise for edge detection, so that image denoising and edge detection are closely related. With the penetration of artificial neural networks and fuzzy techniques in various disciplines, the method of combining classical theory with neural networks and fuzzy logic has become a development direction in the field of image edge detection. Some scholars propose to use neural networks to fuse various feature values to identify image edge detection, and the literature uses BP neural networks to design image edge detection classifiers to discriminate four image edge detection using ten feature quantities of image edge detection images, and the discrimination accuracy reaches 91% on average, but the convergence is slow. The fuzzy inference has no self-learning capability, and the selection of fuzzy rules can only be based on experience with some blindness when applied to image edge detection real-time detection system. Moreover, image edge detection is a multivariate control system, and as the input variables increase, the fuzzy rules will also increase dramatically, the system structure becomes huge, and the complexity of the operation will increase.

2. Relevant Studies

Image denoising is an important aspect of image processing. The image with noise affects the judgment of the staff, and the noise cancellation technology extracts the original image to better interpret the image. At present, the application of fuzzy radial basis neural network transform principle in the field of image denoising has been more common. The fuzzy radial basis neural network denoising method is simple to use and has better quality after image processing. Therefore, it has become a common denoising method. In the development of fuzzy radial basis neural network denoising technology [5], scholars all over the world are constantly researching new denoising algorithms. The literature uses fuzzy radial basis neural network transforms to analyze the data in geology, and then, the fuzzy radial basis neural network transform is used to denoise the image. The literature first proposed the corresponding fast algorithm for fuzzy radial basis neural network transform applied to signal

and image processing and reconstruction. It also proposed the traditional soft threshold function denoising method and hard threshold function denoising method. At the same time, VisuShrink and Sure thresholding formulas, which are more effective in denoising and are widely used, are also proposed. It has created translational invariant fuzzy radial basis neural network denoising [6].

The literature makes improvements in the structure of the functions for soft and hard thresholding denoising by mentioning a thresholding function (semisoft thresholding denoising and Garrote thresholding denoising) that lies in the middle of soft and hard thresholding. Through several simulations, the results conclude that [7] semisoft thresholding denoising and Garrote thresholding have a continuity that is better than hard thresholding denoising and, at the same time, perform better than soft thresholding on the drawback of having a fixed bias. An unbiased likelihood estimation algorithm is proposed in the literature. The knowledge of unbiased risk estimation algorithms is reflected in the articles related to signal denoising and images [8]. The literature proposes a nearest neighbor thresholding algorithm. The very famous BayesShrink is invented based on the combination of both adaptive thresholding and translation invariance. It proposes three methods to improve the soft and hard thresholding functions: polynomial interpolation, soft and hard thresholding tradeoffs, and mode-squared processing methods, which all improve the drawbacks present in the soft and hard thresholding denoising functions. It proposes an improved thresholding function; this thresholding function combines hard and soft thresholding to construct a new class of thresholding function, although it overcomes the problem of constant deviation between the estimated fuzzy radial basis neural network coefficients and the noisy fuzzy radial basis neural network coefficients; its function continuity is poor. Based on the translation-invariant denoising method, an improved thresholding method of fuzzy radial basis function neural network is proposed. This method can not only effectively suppress the phenomenon of "pseudo-Gibbs," which is a discontinuity phenomenon that the signal fluctuates up and down around the specific target, but also can obtain a smaller mean square error compared with the threshold denoising method and improve the signal-to-noise ratio [9]. It improves the traditional correlation denoising method by combining the correlation coefficient denoising algorithm and threshold denoising into a new denoising algorithm. It adopts a denoising method of higher approximation method [9], which makes the disadvantage of the hard threshold function processing method of discontinuity at the threshold well improved. The literature proposes an improved thresholding function and provides unique insights into the selection of thresholds [10], so that the problem of too large thresholds in the first layer which affects the denoising effect is avoided. The threshold function proposed in the literature is between hard and soft thresholding, and changing the parameters of the function is also able to reduce the constant deviation between the estimated coefficients of the fuzzy radial basis neural network and the coefficients of the fuzzy radial basis neural network with noisy signal, and the

function is continuous but its higher order is not derivable in the whole spatial domain of the fuzzy radial basis neural network [11], and the curve is continuous but not smooth transition at the critical threshold X. Many theoretical and applied studies by scholars are proliferating [12].

3. Image Edge Detection Algorithm Based on Fuzzy Radial Basis Neural Network

3.1. Application of Fuzzy Radial Basis Neural Network Algorithm. A fuzzy radial basis neural network is a kind of feedforward neural network with a large amount of information processing and strong fault tolerance, which has the advantages of strong approximation ability, fast convergence, and strong anti-interference ability. It has been proved that radial basis neural network can approximate any nonlinear function with arbitrary accuracy, and the output of radial basis network is linearly related to the connection weights of the network, and the convergence speed is much faster than BP network, and the stability is also good. Although fuzzy radial-based neural networks have the advantages of parallel computing, fault tolerance, and self-learning, they are not suitable for expressing knowledge and cannot make good use of existing empirical knowledge. In contrast, fuzzy logic is suitable for expressing fuzzy and qualitative knowledge with human-like reasoning but lacks self-learning and self-adaptive capabilities [13].

The fuzzy radial basis neural network has structural equivalence with the fuzzy logic system: (1) the basic function of the radial basis neural network is a Gaussian function, which is equivalent to the affiliation function in the fuzzy system; (2) the hidden layer of the radial basis neural network corresponds to the fuzzy inference layer of the fuzzy system, and the number of neurons in this layer is equivalent to the number of fuzzy rules in the fuzzy logic system; (3) the activation function of the output layer of the radial basis neural network is a linear function, which corresponds to the inverse fuzzification of the fuzzy system. Therefore, combining fuzzy logic and radial-based neural network can achieve good complementarity, integrating learning, recognition [14], adaptive, and fuzzy information processing, absorbing the advantages of fast local convergence of radial-based neural network, and using the self-learning of the divine meridian to determine the affiliation function in fuzzy rules; combining the two can better approximate the actual model. The block diagram of the fuzzy radial basis fuser structure of this system is shown in Figure 1.

For the above structure, the 1st layer is the input layer, and the 4 inputs represent the 4 feature values of paper grayscale mean, grayscale standard deviation crease template match, and fractal box dimension, respectively. Layer 2 is the affiliation layer, i.e., the fuzzification layer, where each feature quantity is clustered and normalized using three affiliation functions, S, M, and L, and fuzzified into 3 fuzzy descriptions, large, medium, and small. Based on the fuzzy region division of several feature values, the centroid I and width j of the affiliation function of these feature values can be calculated. There are four groups and 12 neurons in

this layer. The value of the affiliation function of the jth node of the group can be calculated from

$$\text{NET} = \exp\left[-\left(\frac{x-\mu}{\sigma}\right) + \lim_{n\longrightarrow\infty}\frac{1}{n}\sum_{i=1}^{n}X_i Y_i\right]. \qquad (1)$$

Formula (1) in the article is an important formula in the full paper and is the key to the core of the algorithm. The success of this algorithm has a great relationship with this formula. Layer 3 is the fuzzy inference layer, i.e., the fuzzy rule layer. This layer completes the matching of fuzzy rules through the connection with the affiliation function layer. Each node corresponds to a fuzzy rule and completes the mapping of fuzzy rules to the output space. The fuzzy inference uses the product inference method, i.e., the output of the kth node (i.e., the kth fuzzy rule) of this layer is the product of all the input signals of this node. Its formula is as follows:

$$\text{NET} = \sup\left\{\bigcup_{i=1}^{n}X_i\right\} \cdot \sum_{i=1}^{n}X_i Y_i + \frac{1}{n}\left(\frac{x-\mu}{\sigma}\right). \qquad (2)$$

The gradient method is used to adjust the parameters of the fuzzy radial basis neural network; the parameters include the center of the affiliation function of the fuzzification layer, the width, and the connection weights between the regular and output layers. The learning function for the output error of the network is first defined as follows:

$$M = \frac{1}{n}(Y_m - Y_n), \qquad (3)$$

where Y_m is the desired output of the network for the input signal. For the antifuzzification layer, the back-propagation error term is as follows:

$$\theta = \frac{Y_m}{Y_n} - \lim_{n\longrightarrow\infty}\frac{1}{n}\sum_{i=1}^{n}X_i Y_i. \qquad (4)$$

In summary, the parameters of the fuzzy radial basis neural network are self-tuned as follows, after obtaining the corrected values of the adjustable parameters at the nth step of learning:

$$W(n+1) = W(n) + \theta\left(\frac{x-\mu}{\sigma}\right),$$
$$B(n+1) = B(n) + \theta\left(\frac{x-w}{\sigma}\right), \qquad (5)$$
$$G(n+1) = G(n) + \theta\left(\frac{x-b}{\sigma}\right).$$

The fuzzy radial basis fuser realizes online discrimination for image detection in two phases: the fuzzy radial basis fuser learning phase and the image detection discrimination phase, as shown in Figure 2.

After building the fuzzy radial basis neural network, the four eigenvalues of the sample image detection images are calculated, and the gray mean, gray variance, fractal box
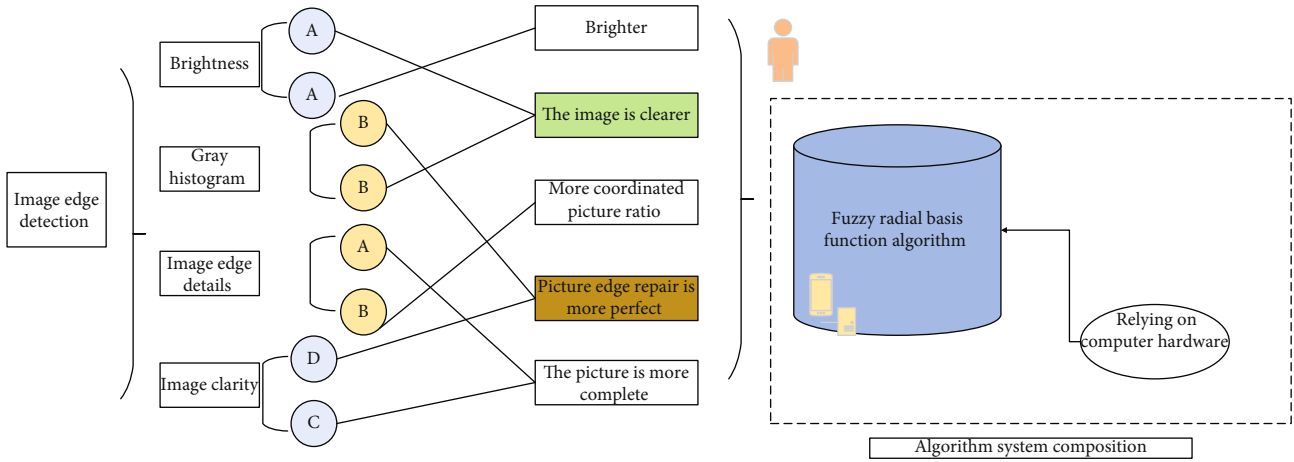
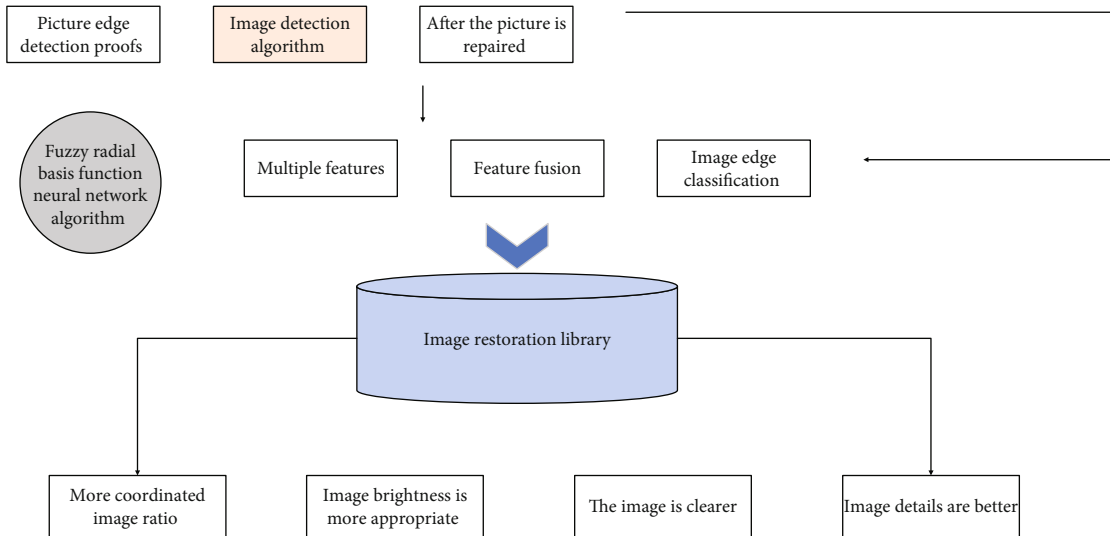Figure 1: Block diagram of the fuzzy radial basis fuser structure.

Figure 2: The implementation process of fuzzy radial basis fusion discrimination for image edge detection.

dimension, and fold template eigenvalues of different image detection are used as inputs to learn and train the fuzzy radial basis fuser, and the training process is the process of self-adjustment of the weight parameters in the network, which requires at least n cycles of adjustment if there are n samples. Through the training process, the network weights of the fuzzy radial basis fuser are continuously adjusted to fit the fusion rules [15].

Unlike previous deep-learning-based image recognition networks, the width learning network of image recognition networks has the advantages of simple structure, small memory, and fast convergence speed. Radial basis [16] width learning network (RBF-BLS) is proposed, and it is composed of two parts, which are RBF nodes and augmentation nodes. The structure is shown in Figure 3.

3.2. Image Edge Detection. Image edge detection is the basic processing method for image interpretation and information extraction. Digital images contain a large amount of infor-

mation, and the extraction of image information is a hot issue in the research field. The edge of the image is the critical point of the gray-scale transformation of digital images. It plays a good auxiliary role in image segmentation and pattern recognition, by the means of gray-scale transformation to recognize the image information. The classical edge detection algorithm is generally through gradient processing to complete the detection of the image, and through [17] the gradient operator using the corresponding template coefficients on the image matrix operations. (1) Filtering: edge detection image in the detection process will be particularly sensitive to noise, and the reason is that the image gradient detection operator is usually used in a derivative way to operate. Therefore, the image needs to be denoised (also called smoothing) before detection.

(2) Enhancement: highlight the accuracy of the image, make the edge detection in the image more suitable for the detection of field gray values, and better distinguish different image information. (3) Detection: after the completion of the
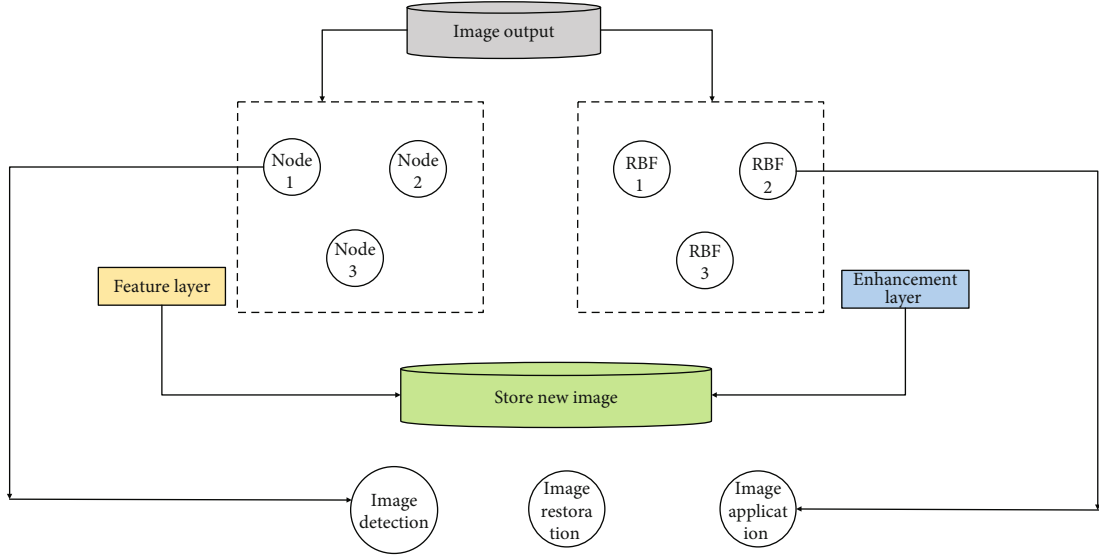
Figure 3: Radial base width learning network diagram.

first two stages, it is the edge detection of the image, many pixels are detected at the edge, and the best threshold is selected to filter the nonedge points. (4) Edge localization connection: since the detected edge information points may be independent individuals, the location of the edge points needs to be judged, from which the orientation of the edge points is detected and connected into a complete edge. The image edge detection process is shown in Figure 4

The classical edge detection operator Sobel operator is a discrete difference operator using pixel convolution [18] operation, which contains $3 * 3$ convolution templates in two directions to convolve the image from horizontal and vertical directions, and the gradient amplitude of the output is obtained by convolving the maximum value in both directions (A is the original image and Gx denotes horizontal detection grayscale and denotes vertical detection grayscale).

$$G(n) = \begin{pmatrix} 1 & 0 & 2 \\ 1 & 0 & 2 \\ 1 & 0 & 2 \end{pmatrix},$$

$$F(n) = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}. \tag{6}$$

Convolution formula is as follows:

$$F(x) = (-1, 2) \cdot (G(x - 1, y - 1), G(x + 1, y + 1)),$$
$$F(y) = (1, 2) \cdot (G(x + 1, y - 1), G(x - 1, y + 1)). \tag{7}$$

Prewitt operator and Sobel operator are both algorithms for edge detection using first-order differential operators. Then, the convolution operation is performed on the image pixel values separately using convolution templates in both directions and the maximum value is taken as the gradient amplitude output.

$$f(x) = \begin{pmatrix} -1 & 2 & -1 \\ -1 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix}. \tag{8}$$

The edge detection technique is the beginning for the image understanding; the evaluation of the edge image is often taken as a subjective analysis, while there is no adaptive evaluation index for the objective evaluation of the edge image. This paper uses the proposed connected region rule to evaluate the merits of the edge detection algorithm. The binary image after edge detection is obtained as edge point A, the number of 4-connected labeled regions B, and the number of 8-connected regions C [19]. The obtained components are analyzed as a ratio to find the values of C/A and C/B. If C/A is smaller, the continuity of the detected edge image will be better and there will be less discontinuity. The principle formula is as follows:

$$\theta = \arccos \theta. \left(\frac{\pi}{2} - \theta \right) + \left(\frac{x - \mu}{\sigma} \right). \tag{9}$$

The smaller the ratio of C/B, the larger the proportion of edges occupied by a single pixel.

In the edge detection experiment of the traditional SAR image edge detection algorithm, the C/A and C/B of the Canny operator are the smallest in the evaluation index, so it can be judged according to the evaluation principle. The Canny operator for noiseless image edge detection is the best among the four classical detection methods, followed by the Sobel operator. For noise-free image edge detection which has good results, the results of edge detection image after denoising the noise-containing image are used to verify the optimal operator in the case of suppressing the noise while keeping the edge as much as possible. In the case of noisy images, the continuity of the Canny algorithm is still good, and the comparison of the edge point data shows that the
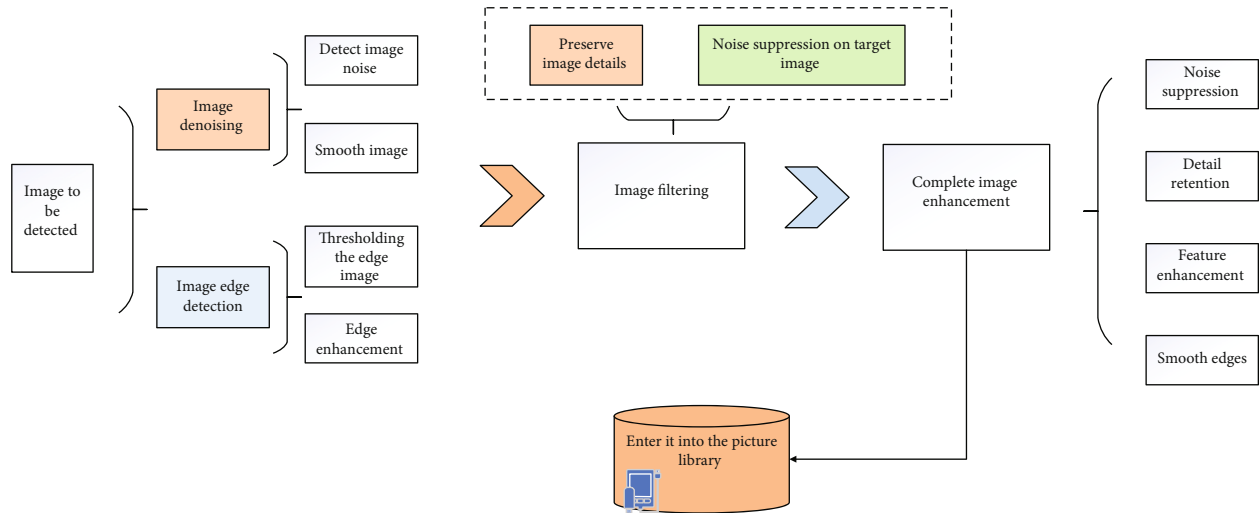
FIGURE 4: Image edge detection process.

Canny algorithm is weak in suppressing noise. The rest of the operators are better at suppressing noise, but the edge retention rate and edge continuity are poor.

In the recent years, fuzzy radial-based neural network transform technology has been widely used in the field of image denoising. The principle of fuzzy radial-based neural network denoising can be regarded as a mathematical function approximation problem, that is, in the function space of the original fuzzy radial-based neural network parent function diffusion, the proposed measure is used to extend the function mapping that can more closely approximate the original signal as well as complete the noise signal distinction. From the signal science point of view, fuzzy radial basis neural network denoising is a filtering problem and compared with the traditional filter, it can better denoise while retaining the integrity of the original signal. Fuzzy radial basis neural network denoising has its unique advantages, which thanks to the characteristics of fuzzy radial basis neural network transform, to achieve good results in the denoising process.

Fuzzy radial basis neural network characteristics are as follows: (1) low entropy: because the coefficients of the fuzzy radial basis neural network decomposition will be sparsely distributed, the entropy value of the processed image will be reduced. (2) Multiresolution: the signal of image noise is well described by the multiresolution approach of the edges, breakpoints, spikes, and other non-smoothness of the image signal. (3) Decorrelation: fuzzy radial basis neural network transform can remove the interference of correlated signals to the image. In contrast, the fuzzy radial basis neural network domain is better than the time domain and it is more effective. (4) Base selection flexibility: the selection of fuzzy radial basis neural network will have different denoising effects on the image. The network transform can make the network base do the best reasonable selection under different environmental factors, to achieve the best denoising effect.

4. Experimental Results and Analysis

4.1. Experimental Results. The proposed improvement method is based on the improvement of RBF (radial basis function) neural network. The RBF network proposed in this chapter is also composed of two parts, including RBF nodes and augmented nodes. The method proposed in this section is equivalent to splitting data by sending part of the data into the RBF nodes and part of the data to the added augmentation layer, which is a good way to avoid problems such as certain errors and getting into local minima that exist in the training of the RBF network. The efficiency is shown in Figure 5.

Since the RBF network uses momentum gradient descent to train the weights from the hidden layer to the output layer, although the gradient descent method has strong convergence ability and the ability to find extreme values, the two gradient descent methods have two disadvantages: first, the gradient descent method needs to consume a lot of computational resources, which requires a lot of computation time, and in the case of high-dimensional data or complex data input, the resources consumed by gradient descent method are undoubtedly huge; secondly, the gradient descent method can fall into local minima, which causes instability of the network.

Based on the above two reasons, the polynomial from the hidden layer to the output layer is split, and the matrix consisting of the i-terms of the polynomial function is combined with the output value matrix of the RBF as the input vector of the augmentation node, which not only allows the data used for augmentation learning in the augmentation layer to preserve the sample features of the dataset itself (i, j-terms of the augmentation layer), such a split can also reduce the RBF network node gradient descent computation, avoid dimensional catastrophe, and other problems. The advantage of this method is that it effectively circumvents the errors and shortcomings of the RBF layers due to the
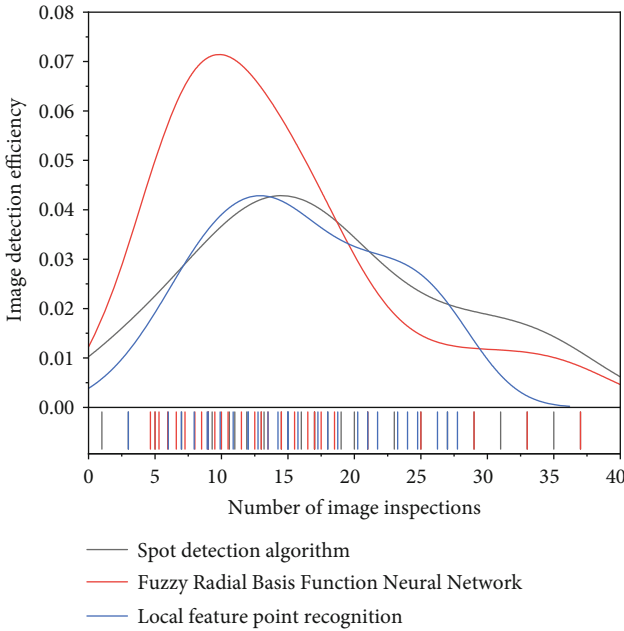
FIGURE 5: Image detection method improvement efficiency change graph.

RBF neural network training, which in turn improves the recognition capability of the network.

4.2. Analysis of Results. The fuzzy radial basis neural network performs fuzzy inference operation according to the above equation, and with the deviation of the output py of the fuzzy radial basis neural network from the desired output PD, the gradient algorithm is used to modify the affiliation center, width value, and the interlayer weights k, p of the second layer of the fuzzy radial basis neural network to complete the training of the fuzzy radial basis fuser. The fuzzy radial basis neural network requires several parameters, here the error tolerance is set to 1, and the system automatically increases the neurons one by one so that the training error gradually decreases until the error is less than the tolerance, and the error decline curve is shown in Figure 6. The final training error reaches 710 orders of magnitude.

Comparing the predicted output value and the expected output value, we can see that they are very close, and the changing trend is the same; the predicted output approximates the array [0,0,0,0,0,1]. From the predicted output, we can judge the image as a bright spot, and the average relative error and the maximum relative error are small, so this fuzzy radial basis fusion can accurately determine the image repair type. After building the fuzzy radial basis neural network, the four eigenvalues of the sample paper disease images are calculated, and the gray mean, gray variance, fractal box dimension, and fold template eigenvalues of different images are used as inputs to learn and train the fuzzy radial basis fuser, and the training process is the process of self-adjustment of the weight parameters in the network, and if there are n samples, at least n cycles of adjustment are needed. Through the training process, the
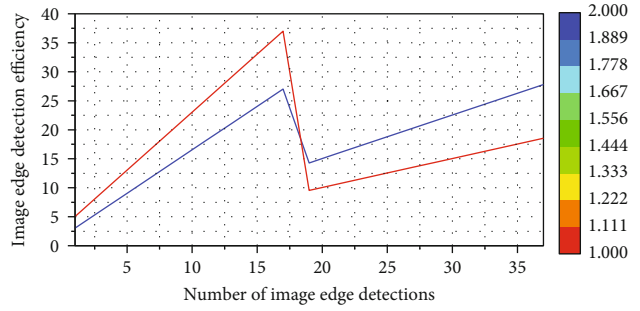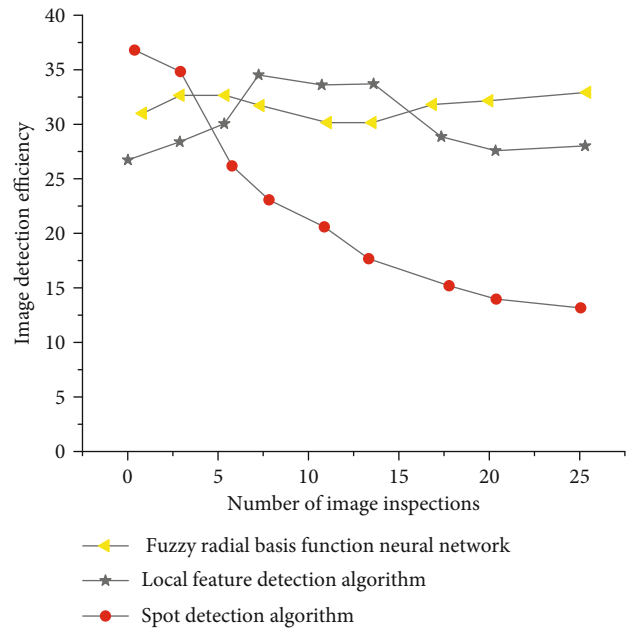

FIGURE 6: Error drop curve.

FIGURE 7: Standard error data graph.

network weights of the fuzzy radial basis fuser are continuously adjusted to fit the fusion rules.

The method of this paper has good detection results for straight lines of different angles, and it can be seen that the maximum error of the method proposed in this paper is below 0.45 pixels, the average error is below 0.1 pixels, and the standard error is around 0.07 pixels; then, the position detection accuracy of the method proposed in this paper has reached an accuracy of around 0.08 pixels, as shown in Figure 7. The average error is below 0.4 degrees, with the standard error around 0.2 degrees; then, the orientation detection accuracy of the proposed method reaches 0.3 degrees.

5. Conclusion

This paper focuses on the image recognition problem based on the fuzzy radial basis neural network learning framework and carries out preliminary research and analysis. The main work and innovations in this paper are as follows: for the RBF-BLS method proposed in this paper, the radial basis

width learning improvement method (RBF-BLS+) is proposed. By minimizing the input data in the input layer and increasing the data in the enhancement layer as much as possible, the overall training speed can be effectively improved. In this paper, the polynomial from the hidden layer to the output layer in the radial basis neural network can be split, and the matrix composed of j, terms of the polynomial function, and the RBF output value matrix can be combined and used as the input vector of the augmentation node, which can not only make the data used for augmentation learning in the augmentation layer preserve the sample features of the dataset itself (the j-term data of the augmentation layer) but also effectively circumvent the input layer because of the RBF neural network training that has some errors and shortcomings (the PRBF neural network itself has some errors and problems in training).

The study of image recognition techniques is an extremely complex technical project, and due to the limited personal ability and time, the research in this paper is rather superficial, and much work remains to be explored in further depth.

The subsequent research work in this paper can be carried out in the following aspects: adding radial basis neural networks to the width learning framework. The matrix composed by j can be subjected to an appropriate preprocessing process before being sent to the enhancement layer to improve the recognition correctness of radial basis width learning networks for image recognition or classification.

Due to the fast nature of width learning methods, currently, people are only concerned with the learning effect of the model (recognition rate, timeliness, and memory occupation) whether they are learning and researching on deep learning frameworks or width learning frameworks for image recognition.

Nowadays, people are especially concerned about life and health issues in a special period. The research on width learning-based image recognition technology should keep pace with the times and can be useful in fast medical image recognition, such as fire monitoring, lung CT image diagnosis, infrared image thermometry, and other applications, by using its features of high recognition accuracy and good real-time performance. The algorithm used in this paper can detect the edge of the image to a certain extent, can better recognize the image, and can continue to improve its recognition accuracy in the future development process.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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