Scholar Publishing Group
International Journal of Neural Network
https://doi.org/10.38007/NN.2022.030407
ISSN 2790-2692 Vol. 3, Issue 4: 52-60

Image Features Fused with BP Neural Network

Zhanwei Feng*

Department of Information Engineering, Heilongjiang International University, Harbin 150025, China

fengzhanwei1981@126.com

**corresponding author*

Keywords: BP Neural Network, Image Feature, Genetic Algorithm, Image Fusion

Abstract: Because of the remarkable advantages of computer neural network(NN), it has been widely used in the field of image feature(IF) fusion recognition, and the research involves multiple research fields. In addition to image recognition or image classification, it has been studied in computer vision, industrial control and other aspects. This paper focuses on the analysis of the IF of the fusion BP NN. This paper briefly analyzes the fusion of IF, spectral features and texture features, proposes BP NN algorithm, and applies it to image fusion design; Finally, through experimental tests, the detection accuracy of fusion BP NN and traditional BP algorithm in IF fusion is compared and analyzed, which verifies the effectiveness and feasibility of the BP NN algorithm in this paper.

1. Introduction

IF extraction is a very important part of pattern recognition. For many image recognition and computer vision problems, the solution is based on representing useful information about the image, that is, using a single unit to represent the entire image. IF extraction plays an important role in image processing. Although the genetic algorithm has the ability of global search, there will be many different extreme values in the evolution process of the genetic algorithm, which makes the convergence speed of the network too fast and premature. Although the image eigenvalue is used as the input of the network, the calculation of the network is still large. Therefore, this paper studies and analyzes the IF by fusing BP NN.

Many scholars at home and abroad have studied and analyzed the IF of fusion BP NN. Maurya S proposed a new feature extraction method, which fuses manual features and advanced features, and then extracts/selects features from the fused features. Manual features based on local energy are obtained from empirical mode decomposition, and advanced features are extracted from deep NNs. A method to reduce a large number of data points in the sample is also proposed. This scheme studies the influence of the number of extracted/selected features. Three case studies verify the effectiveness of the proposed scheme [1-2].

This paper first introduces the data fusion(DF) technology of image processing and BP NN algorithm, and applies the BP NN algorithm to IF fusion for analysis. The strong randomness of the initial value of the weight of genetic algorithm is also easy to cause slow convergence speed and fall into the missing point of local minimum point. In this paper, the BP NN with global search capability is used to solve the initial connection weight training, which reduces the search interval, It gives full play to its advantages of global optimization, and the experimental results also prove that the classification ability of fused images has been improved reliably and significantly, and the generalization ability of the network has been improved [3-4].

2. Research on Fusion IF

2.1. DF Technology for Image Processing

DF is mainly aimed at the fusion of multi-source data. The fusion of multi-source remote sensing image data is an important part of DF. Jia Yonghong and others put forward the concept of multi-source remote sensing image DF, that is, to complement or gather redundant information on multi-source remote sensing data of the same ground object or regional environment. The DF not only has the advantages of the original image, but also reduces the fuzziness of recognition, effectively improves the overall analysis ability, and can meet more different application requirements [5-6].

2.1.1. Pixel level DF

Pixel level DF is the summation analysis of the data of the corresponding pixels in the collected multiple original images. The obtained pixel fusion images can supplement and strengthen the useful information in the original images, and provide a basis for image enhancement, image further analysis or classification, and human interpretation. It is also the early foundation for further feature level or decision level fusion, and is the lowest level DF [7]. The fusion model is shown in the figure below. Pixel level fusion can retain as much fine information as possible in the original data. Pixel fusion is the lowest level of fusion processing. The analysis ability, error correction and anti-interference ability of the fused image are poor. The process is shown in Figure 1 [8-9].

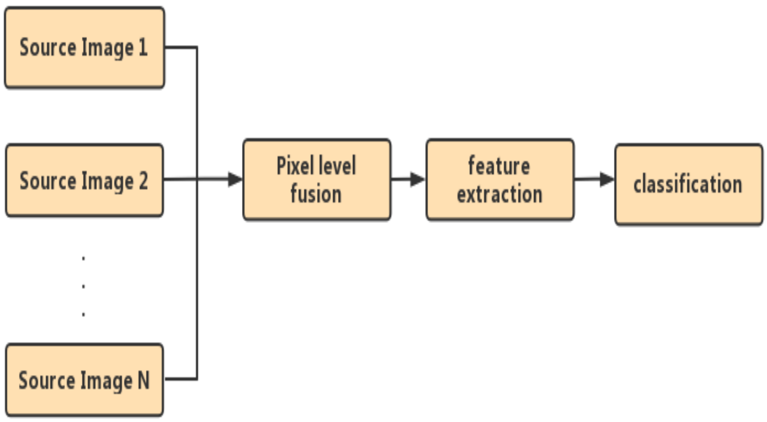

Figure 1. Pixel level fusion process

2.1.2. Feature Level DF

The main advantages of feature level DF can effectively compress and process data in real time. This fusion belongs to the middle level of fusion technology, and the accuracy of feature extraction directly affects the use of decision level fusion [10].

2.1.3. Decision Level DF

The use of decision level fusion is based on the specific application requirements. Its input is the extracted feature information, and the result is the decision speed through the decision rules. The requirements for IF extraction data are very high. Decision level fusion can use data obtained from homogeneous or heterogeneous sensors, and the strong analytical ability can fully reflect the information of targets and environments, meeting the needs of different application purposes [11-12]. Decision level fusion is the highest stage of fusion. It has high requirements for image preprocessing or feature extraction, so the amount of decision calculation is relatively large.

2.2. Fusion of Spectral Features and Texture Features

The spectral features and texture features are extracted for feature combination and fusion. The method of feature combination can better highlight the details of the data in the image. Here is a simple improvement on the feature fusion in Wang Zhiyuan's paper [13]. The following is the process of feature fusion as shown in Figure 2.

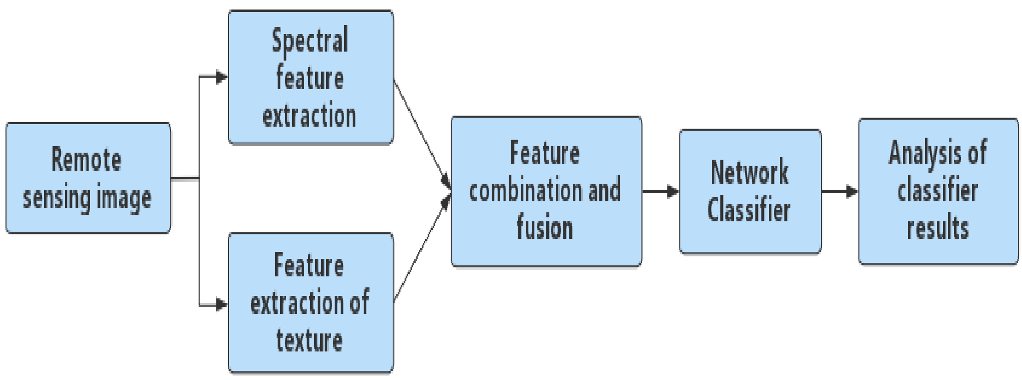

Figure 2. Fusion process of spectral and texture features

In the process of texture feature extraction, texture mainly reflects the gray level distribution. We also extract the gray level co-occurrence matrix by windowing according to the similar method of extracting the spectral gray level average feature. Then, after calculating the gray level co-occurrence matrix of each windowed pixel, calculate the average energy value and average correlation value of each windowed pixel according to the previous calculation formula of energy and correlation characteristics [14-15].

3. BP NN

Topology of NNs NNs can also be called feedforward networks, it is a directed acyclic topology.

BP NN structure is a multilayer feedforward network trained by error back propagation algorithm. The advantage of applying BP NN algorithm to image restoration is that we do not need to describe the degradation function in detail, but directly restore the degraded image by training BP NN, trying to achieve satisfactory results [16]. The basic BP NN has at least three layers, namely, input layer, hidden layer and output layer, as shown in Figure 3:

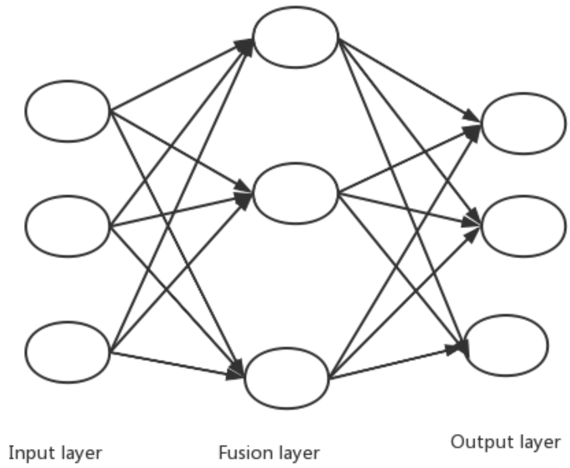

Figure 3. BP NN structure diagram

The operation mode of BP NN is formed through the learning process in two directions. These two directions are respectively the forward signal propagation process and the reverse error signal propagation process. An input signal first enters the input layer of the BP NN from the outside, and then enters the middle layer of the BP NN through the input layer, which is generally called the hidden layer, until it propagates forward to the output layer to give results. When the output signal fails to reach the expected output preset by us, the signal will start to propagate in reverse and return the error between the expected output and the actual output via the original line [17-18]. On the way back, the BP NN will carry out the connection weights between all levels, thus reducing the feedback error. If the above process does not reach the preset expected output, it will iterate repeatedly in the BP NN, and finally the output of the signal will be less than the expected value, and then the signal will be output through the output layer, as shown in Figure 4.

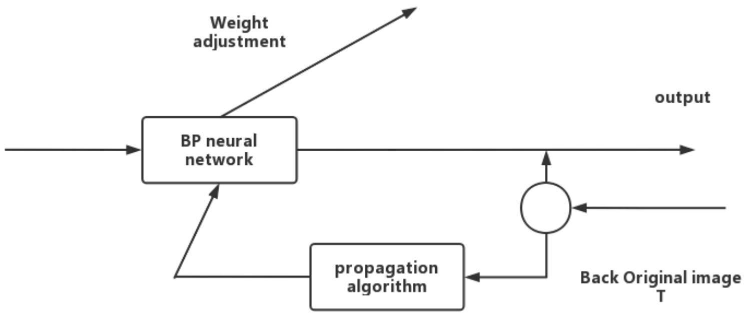

Figure 4. Learning Process of BP NN

It can be seen from the description of the learning process of BP NN for image restoration that whether a reasonable BP NN system can be built is the key to determine whether a satisfactory image restoration result can be obtained.

As shown in Figure 3, the BP NN will be at least a three-layer structure. Therefore, it is assumed that the BP NN to be constructed consists of N input neurons in the input layer, K hidden layer neurons in the hidden layer, and M output neurons in the output layer. We can set 01qk as the output value of the hidden layer, and 02qm as the output value of the output layer. Then set the input learning sample as xqm, and the corresponding expected output value is the value given by tqm.

The specific algorithm is as follows: input the qth sample (xq={aq1, xq2,... xqn}) into the network in order, and calculate according to the following formula:

$$01_{qk}\{i\} = g(\sum_{n-1}^{N} W1_{nk}(i)x_{qn})$$
$$02_{qm}(i) = g(\sum_{k=1}^{k} w2_{km}(i)01_{pk}(i)) \qquad (1)$$

The activation function used in the calculation is often an S-type sigmoid function,

$$g(x) = 1/(1+e^{-x}) \qquad (2)$$

Formula for calculating square error:

$$E = \frac{1}{M}\sum_{m-1}^{M}(t_{qm} - 02_{qm})^2 \qquad (3)$$

If E $\leqslant$ ε, Stop the iteration, or go to the next step.

The above is the mathematical expression of each neuron of BP NN and forward and backward signal propagation algorithm. Although BP NN has the self-organizing learning ability expected by design, it also has significant defects: BP algorithm reduces the route convergence according to the gradient of mean square deviation, but the gradient line of deviation has many local minimum points, leading to the NN will enter the minimum point; The convergence rate of BP learning algorithm is not fast enough, which may consume too much time; The number of hidden layer nodes is not easy to establish a reasonable value. Considering the above problems, the BP algorithm should be adjusted accordingly, so that it can accurately process the input without learning and improve the convergence rate.

4. Experimental Research on IF Fusion Based on BP NN

4.1. Experimental Design

The experiment is divided into two scenarios: based on the fusion BP NN parameter optimization experiment, the method proposed in this paper is compared with the traditional BP learning algorithm; In the feature level image fusion experiment, the BP NN constructed by this method is applied to the feature level image fusion, and the results are compared with those obtained by other fusion methods.

4.1.1. Acquisition of Experimental Data

The data acquisition process is as follows: select a standard image, and conduct left and right blur processing respectively to obtain two source images; Perform 20 operations on source images respectively $\times 20$ size window segmentation, and extract the region definition information of each segmented image block respectively.

4.1.2. BP Network Platform

When BP NN is used for supervised image classification, the input signal of the network is the fusion feature of the image. The network trains the image according to certain rules, and the input signal is the image classification. The network training rules or methods adopt a 3-layer network structure. The input layer nodes are selected as 3 eigenvalues, while the number of hidden layer nodes is determined as 12 nodes according to the actual experimental statistics to calculate the convergence speed of the network and the classification accuracy of the overall network. According to the definition of BP network, the training process of the network is divided into two processes: forward propagation and reverse error propagation. The propagation between adjacent layers is unidirectional, that is, the calculation results of neurons in each layer only affect the neurons in the next layer. The calculation function of each layer is the S-type function with nonlinear amplification gain as the activation function of the node. The function formula is:

$$g(x) = \frac{1}{1+e^{-x}} \tag{4}$$

When a group of training samples are input in the network, and the output result does not meet the output expectation, we define a function for error adjustment. The function formula is as follows:

$$E = \frac{\sum_{k=0}^{N-1}(d_k - y_k)^2}{2} \tag{5}$$

BP NN method is to learn sample data and find a mapping relationship between input and output, and this mapping relationship is actually the determination of weights, which can also be said to be the extraction of input data features. But we determine the initial weight value through genetic algorithm. Then the work of BP network is to classify the image data to be recognized. The software we use is that its toolbox contains a BP network constructor for creating backpropagation. The initial weight value obtained by the genetic algorithm is the individual that makes the network output have the minimum error in the last iteration of the algorithm. It is brought into the BP network for sample training. The same sample data as that used for BP training is used to test the classification accuracy of the two algorithms and the generalization ability of the network.

4.1.3. Feature Collection Image Fusion

This section is the experimental part of feature level multi focus image fusion. The problem of multi focus image fusion has been transformed into the problem of classification according to the characteristic value. This section uses the standard map as an example of experimental data. The BP NN fusion algorithm fuses the image, uses the improved PSO method of Gaussian membership to fuse the image, and uses the improved PSO method of triangular membership to fuse the image.

4.2. Evaluation of Classification Results

In order to quantitatively evaluate the classification effect of various methods, we selected 500 pixels as our sample data according to the actual data, established the hybrid matrix, and then estimated the two different parameters, the overall classification accuracy and Kappa coefficient, according to the hybrid matrix. The calculation results are shown in the following table. It can be seen from the classification method results that the classification accuracy has been improved by more than 10% when genetic algorithm is added to the BP NN, However, when we talk about the extraction and fusion of image spectral features and texture features, the overall accuracy of the classification of fusion features is more than 15% higher than that of the simple use of BP NN, more than 5% higher than that of the improved algorithm not based on fusion features, and the overall classification time is also significantly improved. Therefore, for image classification, we extract and synthesize IF information, which is very good for the classification of complex ground objects. The classification effect is shown in the figure. The accuracy comparison of the three classification methods is shown in Table 1 and Figure 5.

Table 1. Data sheet of classification effect test

	BP NN	GA-BP algorithm	GA-BP algorithm for fusion feature classification
Overall classification accuracy	73.46%	81.53%	88.43%
Kappa Coefficient	0.6423	0.7423	0.8532

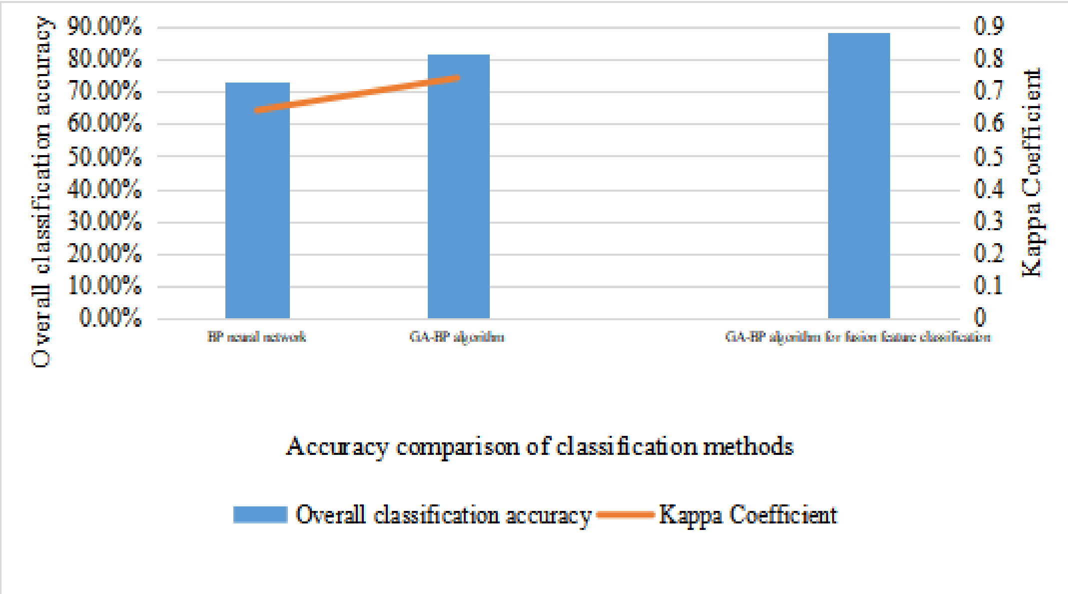

Figure 5. Accuracy comparison of classification methods

It can be found that it is impossible to distinguish the effect of the fusion medium with the naked eye, and various fusion methods have completed better multi focus image fusion. Through comprehensive analysis, the fusion evaluation of feature level fusion algorithm is 50% higher than that of pixel level fusion results in terms of peak signal-to-noise ratio. This is because the processing level of feature level image fusion is higher than that of image # level fusion algorithm, and the fusion is more reasonable.

From the mean square error and mean absolute error data, it can be seen that the error of the original image of feature level fusion is very small, and better multi focus image fusion is achieved; The BP NN method proposed in this paper has better global search ability and local fast convergence characteristics than the traditional BP learning method.

5. Conclusion

This paper studies the IF based on the fusion of BP NN. Although this method effectively improves the classification accuracy of images, it still needs to be improved. In the process of IF extraction, only the main feature information is extracted, and the detailed feature information of the image is ignored, which will also affect the classification accuracy of the image, and the selection of feature fusion methods will also vary according to the specific image. Although BP NN algorithm has more global convergence ability than other traditional search methods, it is easy to fall into the local minimum problem when this method is used to solve the network initial weight training. Because the target search method is uncertain, the search ability of BP NN still cannot solve the target problem; Image classification is becoming more and more important in various applications of images, so more in-depth research on image classification technology is needed. The development of fusion technology has greatly improved the classification of images. IF based on fusion BP NN need further improvement and research.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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