Automatic Target Recognition Technology of SAR Images Based on 2DPCA+PNN

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Abstract. In this paper, the SAR image in MSTAR data is used as the research object. The target recognition algorithm based on probabilistic neural network (PNN) is mainly studied. It includes three parts: SAR image preprocessing, feature extraction, classification and recognition. Lee filtering and adaptive threshold method are used to filter the speckle noise effectively, and the 2DPCA principal component analysis method is used to reduce the dimension of the image and obtain the 10 dimensional image features. The recognition part is input to the PNN training test with the acquired feature vectors, and the 85.17% correct recognition rate is obtained, and the target classification and recognition of the SAR image is completed.

Keywords: SAR; Image recognition; SAR image processing; Feature extraction; PNN network.

1. Introduction

Synthetic Aperture Radar (SAR) is an effective means of observing the earth. With the continuous enlargement of the scale of SAR image data and the characteristics of SAR images, the method of manual interpretation has become very difficult. SAR image automatic recognition technology has entered the field of vision. This paper starts from three parts: SAR image preprocessing, feature vector extraction and classification and recognition methods. Research on automatic identification of SAR images.

First, image preprocessing.

In real world, SAR images contain not only the targets that need to be identified, but also the large amount of clutter produced by human or natural causes. The preprocessing of SAR images is to extract the target objects from the clutter background, and the SAR system works to make the images have strong speckle noise[1,2]. And the speckle noise belongs to multiplicative noise. Therefore, Lee filtering and adaptive threshold method are used to preprocess the SAR image, and then the optimal scheme is selected.

Second, SAR image feature extraction algorithm simulation and analysis

Image processing is generally a two-dimensional data set of 128*128, which is directly used for PNN network input. The increase of input nodes will lead to the complexity of PNN network design. Therefore, we need to use Bi-2DPCA(Bi-2DPCA, bilateral two-dimensional principal component analysis) to reduce the dimension. 2DPCA method is used to compress the SAR images along the row direction to remove redundant pixels between rows, and then calculate the mean and covariance of training image samples. Then we get the best row projection matrix, and finally get the row 2DPCA characteristic matrix of the training sample image[3]. The dimension of the Bi-2DPCA characteristic matrix can be determined by the row and the column together. So we can control the dimension of the
feature matrix more precisely, and then select the best dimension target feature to improve the efficiency and accuracy of SAR image recognition. The 2DPCA matrix is the best row projection matrix.

Third, SAR image recognition
We make use of PNN network to form a classifier and PNN, which is simple in structure and used in many fields. PNN network has great advantages over traditional BP networks. For example, the performance of the classifier is good. When adding recognition classes, it does not need to study for a long time. The convergence speed is fast, and it is easy for hardware implementation. There is no need for continuous training of the network. The number of neurons in each layer is relatively fixed, and the parameters of the whole network need to be adjusted less, which makes it easier to adjust the classification performance of the whole network.

We use the MSTAR data as the research object. Experiments show that this method can effectively improve the accuracy of SAR image recognition.

2. Target Recognition Based on 2DPCA and PNN

2.1. Image Preprocessing

2.1.1. Lee Filtering
The working mode of the SAR system causes the image to have strong speckle noise. In the information returned by the radar, the gray value of the adjacent pixels will have some indeterminate changes due to the coherence of the SAR image, and the change is based on a special mean value. The Lee filter can effectively filter the speckle noise of SAR images, and the speckle noise of SAR images belongs to multiplicative noise. The size of the noise will change with the change of the signal, aiming at the particularity of multiplicative noise. We choose the Lee filter. Lee filter to filter the speckle noise of the SAR image according to the statistical characteristics of the image part. The Lee filter is based on the fully developed speckle noise model. We select a certain range of window in the image area as the research part. At the same time, we assume that the prior variance and the mean value are approximately equal to the mean and variance of the research part.

\[ \hat{U} = C\overline{U} + DW \]  
\[ C = 1 - \frac{VAR(U)}{VAR(W)} \]  
\[ D = \frac{VAR(U)}{VAR(W)} \]  
\[ \hat{U} = \overline{W} + D(W - \overline{W}) \]  
\[ VAR(U) = \frac{VAR(W) - \sigma_w^2 \overline{W}^2}{1 + \sigma_w^2} \]  
\[ \sigma_w^2 = \frac{1}{N} \]

2.1.2. Adaptive Threshold Method
The adaptive threshold method (Maximum variance) is also called the largest class variance method. Its function is to distinguish the background and the two parts of the target in the SAR image according to the gray value of each pixel of the SAR image. It calculates the background and the location of the target in the SAR image by calculating the variance between classes. When the variance between the two classes is the largest, the difference between the background and the target's gray level is bigger. We make the threshold \( u \) and \( Y \) to identify the ratio of the number of pixel points to the number of pixels of the whole image, and the average value of the gray value of the target recognition is \( a \), \( Z \) is the ratio of the number of pixels to the number of pixels in the whole background. The average value of the
background gray value is B, the inter class variance is D, the SAR image size is x*y, P is the number of pixels below the threshold value, and the Q is the number of pixels whose gray value is higher than the threshold value. The average gray value of the whole image is regarded as K, and then we can get:

\[ y = \frac{q}{x \times y} \]  \hspace{1cm} (6)

\[ Z = \frac{p}{x \times y} \]  \hspace{1cm} (7)

\[ p + q = x \times y \]  \hspace{1cm} (8)

\[ k = Y \times a + Z \times b \]  \hspace{1cm} (9)

\[ d = Y \left( a - k \right)^2 + Z \left( b - k \right)^2 \]  \hspace{1cm} (10)

Then the traversal method is used to find the maximum value of the variance between the classes.

2.2. DPCA Feature Extraction

2DPCA (2DPCA, two-dimensional principal component analysis) is the traditional PCA algorithm after upgrading\(^7\). When using the 2DPCA algorithm to find covariance matrix, the data amount of computation is far less than the amount of data calculated by using PCA covariance matrix. Because of the short computation data, the processing time is shorter. 2DPCA and PCA algorithm are basically a principal component method. We assume \( B_j \), \( j = 1, 2, \ldots, M \) is the total number of sample images. First we must calculate the covariance matrix \( H \) of the image.

\[ H = \frac{1}{M} \sum_{j=1}^{M} M \left( \hat{B}_j - \hat{B} \right) \left( \hat{B}_j - \hat{B} \right)^T \]  \hspace{1cm} (11)

\[ \hat{B} = \frac{1}{M} \sum_{j=1}^{M} B_j \]  \hspace{1cm} (12)

After obtaining the covariance matrix, we need to determine its characteristic points and their corresponding values, then calculate their eigenvectors, and then select the eigenvectors whose cumulative contribution rate reaches 0.9 to 0.99, so that the selected feature vectors can be dispersed as much as possible. We should try to select the feature vectors with larger eigenvalues and reconstruct the best projection matrix by using these eigenvectors. Assuming that the original image size is \( x \times y \), after 2DPCA processing, the image is reduced to \( x \times n \), and \( N \) is determined according to the range of eigenvalues of the selected values\(^8\). We reduce the dimension of the column number of the image. Through the above analysis, we can freely select \( n \), that is, the number of extracted features, so that we can select the best target characteristics, in order to improve the recognition rate and accuracy.

2.3. Design of PNN Network

In 1990s, D.F.Specht proposed the Probabilistic Neural Networks (PNN, probabilistic neural network)\(^9\). PNN network to extract and classify the SAR images by using the feature vectors extracted from SAR images\(^10\). The principle of Bayes decision making is mainly used. Bayesian decision theory is based on only knowing part of the image data. The unknown image data are estimated by subjective probability, then the probability of occurrence is corrected by the Bayes formula. Finally, the best choice is made according to the expected value and the probability of occurrence after correction. Therefore, PNN network makes full use of statistical knowledge for target classification. It has great advantages in the field of classification and recognition. PNN networks are generally divided into four layers: input layer, mode layer, summation layer and output layer.
From this network model, we can see that picture data can only flow forward in the network, and there is no feedback link in the whole network. The function of the pattern layer is the weighted summation of the image data from the input layer. Then, a nonlinear operator is used to compute the summation result, and finally the good data is sent to the summation layer. The number of the nodes in the layer is determined by the number of input image eigenvectors and the categories that need to be identified. We use the Gauss function as the general nonlinear operator in the pattern layer.

$$\theta = \exp - \frac{\sum ((x-c_i)^2)}{2 \sigma^2}$$

(13)

$C_i$ is the mean value of the radial distance from the sample feature vector to the data center, and the sigma component is the corresponding switching parameter. The correlation degree between the unknown data and the standard data can be obtained by using this characteristic function. Each node of the summing layer has corresponding mode units, and the direct connection between them is unique and one-to-one[11]. The units of the summation layer are calculated according to the Parzen method to estimate the probability of each category.

$$p(x|y_i) = \frac{1}{n^{\frac{m}{2}}} \frac{1}{\sigma^n} \sum_{i=1}^{n} \exp - \frac{(x-x_i)^T (x-x_i)}{2 \sigma^2}$$

(14)

In this formula, $C_i$ is a category, $x$ is a sample feature vector, $X_i$ is a pattern sample of category $I$, in PNN, we regard it as a weight, $M$ is the dimension of a vector, the smoothing parameter of a network is a sigma, and the number of pattern samples of $I$ class is $nP(x)$, which is a prior probability. The number of output layer elements is consistent with the number of categories to be identified. According to Bias criterion and the input feature vectors of each class, we estimate the risk of which category is the smallest.

$$P(x|c_i)P(c_i) > P(x|c_j)P(c_j)$$

(15)

The $I$ in the formula is not equal to $J$, and the output is:

$$y = c_i$$

(16)

To sum up, we can see that the PNN network has less computation and less network adjustment parameters. It only needs to adjust the smoothing factor to achieve the purpose of regulating network performance. Generally speaking, we can give a smoothing factor based on experience when constructing PNN network.

3. Identification Process and Analysis

3.1. Experimental Images

The SAR image used in the study is derived from the MSTAR dataset. The image size is 128*128. There are three kinds of SAR images, BMP-2, btr-70 and T-72 respectively. The number of SAR images used is shown in Table 3.
3.2. Recognition Process
This recognition method first preprocesses the image by Lee filtering and adaptive threshold method, filters coherent noise, and distinguishes the background from the recognition target. Then the processed image is extracted by 2DPCA principal component analysis, and the extracted features are sent to the PNN network for classification and recognition.

3.2.1. SAR Image Preprocessing
Under normal circumstances, SAR images contain a large number of background clutter besides target objects, which seriously affect the accuracy of feature extraction and recognition. After processing SAR images by Lee filtering and adaptive threshold, we can filter out background clutter and help to improve the recognition accuracy. OSTU is Maximum variance\cite{12}.

The results of image pre-processing of three kinds of SAR images are as follows:

\begin{figure}[h]
\centering
\begin{subfigure}{0.3\textwidth}
\includegraphics[width=\textwidth]{fig2.png}
\caption{btr-70 diagram.}\label{fig2}
\end{subfigure}
\hfill
\begin{subfigure}{0.3\textwidth}
\includegraphics[width=\textwidth]{fig3.png}
\caption{BMP2 diagram.}\label{fig3}
\end{subfigure}
\hfill
\begin{subfigure}{0.3\textwidth}
\includegraphics[width=\textwidth]{fig4.png}
\caption{T72 diagram.}\label{fig4}
\end{subfigure}
\caption*{Figure 2. \textbf{BTR-70} diagram. \quad Figure 3. \textbf{BMP2} diagram. \quad Figure 4. \textbf{T72} diagram.}
\end{figure}

3.2.2. SAR Image Feature Extraction
2DPCA is a two-dimensional principal component analysis.2dPCA, which can be directly processed on the basis of two-dimensional images\cite{13}. This method can not transform the two-dimensional image matrix into one dimensional image matrix in advance.

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{fig5.png}
\caption{2DPCA processing diagram.}\label{fig5}
\end{figure}

Image images with training set feature extraction:

\begin{figure}[h]
\centering
\begin{subfigure}{0.4\textwidth}
\includegraphics[width=\textwidth]{fig6.png}
\caption{Image before feature extraction.}\label{fig6}
\end{subfigure}
\hfill
\begin{subfigure}{0.4\textwidth}
\includegraphics[width=\textwidth]{fig7.png}
\caption{Image after feature extraction.}\label{fig7}
\end{subfigure}
\caption*{Figure 6. \textbf{Image before feature extraction.} \quad Figure 7. \textbf{Image after feature extraction.}}
\end{figure}

As shown in the figure, we extract features from 10 images in the training set using 2DPCA, and extract 10 feature vectors from each image. The ordinate represents the position of ten images. The abscissa is the feature vector extracted from each image. Since the adaptive threshold value method is used in the preprocessing part, the image has only two gray values. According to the image image before and after feature extraction, we can see clearly.We reduce the column vector from 128 dimensions to 10 dimensions, that is to say, we successfully extract 10 eigenvectors of 10 images.

2DPCA feature extraction results:

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
\textbf{Recognition category} & \textbf{Number of training sets} & \textbf{Number of test sets} \\
\hline
BMP-2 & 100 & 300 \\
BTR-70 & 100 & 200 \\
T-72 & 200 & 200 \\
\hline
\end{tabular}
\caption{Training samples and test samples.}
\end{table}
3.2.3. Classification and Recognition

In order to verify the correctness of the classification, ten feature vectors of ten images from each class of SAR images extracted from 2DPCA are used to train the PNN network. In order to verify the correctness of the classification, ten features of one class of images are extracted, and the input nodes of the PNN network are set to 10, and the output nodes are set to three.

![Figure 10. PNN classification diagram.](image)

In this image, red is the classification of prediction, and blue is the actual classification. According to this image, we can see that the red dot and the blue dot coincide completely, which means that the PNN network training is successful, and the 40 images are divided into three categories, third of which have two sets of images, which conform to our previous design. The correct rate of classification is 100%.

**Table 2.** Identification result analysis table.

| Recognition category | Number of training sets | Number of test sets | Accuracy rate | Total recognition rate |
|----------------------|-------------------------|---------------------|---------------|-----------------------|
| BMP-2                | 100                     | 300                 | 80.56%        | 0.8571                |
| BTR-70               | 100                     | 200                 | 92%           | 0.8571                |
| T-72                 | 200                     | 200                 | 84%           | 0.8571                |

From the table, we can see that we divided 400 training images and 700 test images into several groups for classification and recognition. Each group classifies and identifies three kinds of SAR images, BMP-
2, btr-70 and t-72. respectively. We select 10 pictures of each class to form training sets, extract feature vectors and use PNN network to learn, and draw a network model for recognition. In the test samples, 300, 200 and 200 images were taken for each class of SAR images. The trained network model was used for classification and recognition, and the correct rate was 85.71%.

4. Discussion and Analysis

In order to further verify the effectiveness of the method, the authors extract the texture features based on gray level co-occurrence matrix. First, the gray level of the image is compressed to 16 levels, and the distance is 1. From the four directions of 0 degrees, 45 degrees, 90 degrees and 135 degrees, 4 symbiotic matrices are calculated. After the normalization of the symbiotic matrix, the parameters of texture, such as energy, entropy, moment of inertia and correlation, are calculated. The mean and standard deviation are calculated as the final 8 dimensional texture feature values. The following table shows the special vector group obtained by hb15279.

Table 3. HB15279 texture characteristic parameter matrix.

| direction | energy       | entropy       | Moment of inertia | Relevance | mean value | standard deviation |
|-----------|--------------|---------------|-------------------|-----------|------------|-------------------|
| 0         | 0.018101     | 4.428291      | 6.362453          | 0.075708  | 0.016966   | 0.001332          |
| 45        | 0.015808     | 4.548775      | 9.662177          | 0.049087  | 4.488083   | 0.070876          |
| 90        | 0.018138     | 4.425138      | 6.310449          | 0.076086  | 8.014639   | 1.938083          |
| 135       | 0.015816     | 4.550127      | 9.723478          | 0.048593  | 0.062368   | 0.015624          |

The mean and standard deviation are calculated as the final 8 dimensional texture feature vectors through the above table. The PNN network is trained by the texture feature and classified and identified. The blue point is the result of PNN network recognition. The average recognition accuracy is 0.7222, which shows that 2dpca+pnn's recognition algorithm is better than glcm+pnn recognition algorithm.

Figure 12. Texture feature PNN result diagram.

5. Conclusion

According to the characteristics of SAR images, this paper proposes an automatic recognition algorithm for SAR images based on 2DPCA and PNN networks, and verifies the effectiveness of the method. The method specifically includes SAR image preprocessing based on LEE filtering and adaptive threshold method, and feature extraction based on 2DPCA. And the three parts of classification and recognition based on PNN. Lee filter and adaptive threshold method are used to filter the speckle noise effectively. The 2DPCA principal component analysis method is used to reduce the dimension of the image and get the 10 dimensional image features. The recognition part is input to the PNN training test with the acquired feature vectors, and the 85.17% correct recognition rate is achieved, which achieves the SAR image target classification and recognition better.

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