Research Article

SAR Target Recognition via Monogenic Signal and Gaussian Process Model

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The monogenic signal and Gaussian process model are applied to synthetic aperture radar (SAR) target recognition. The monogenic signal is used to extract the features of the SAR image. The Gaussian process model is a statistical learning algorithm based on the Bayesian theory, which constructs a classification model by combining the kernel function and the probability judgement. Compared with the traditional classification model, the Gaussian process model can obtain higher classification efficiency and accuracy. During the implementation, the monogenic feature vector of the SAR image is used as the input, and the target label is used as the output to train the Gaussian process model. For the test sample to be classified, the target label is determined by calculating the posterior probability of each class using the Gaussian process model. In the experiments, the validations are carried out under typical conditions based on the MSTAR dataset. According to the experimental results, the proposed method maintains the highest performance under the standard operating condition, depression angle differences, and noise corruption, which verifies its effectiveness and robustness.

1. Introduction

Synthetic aperture radar (SAR) realizes the observation of the focused area through high-resolution imaging for intelligence interpretation. SAR target recognition classifies image chips of unknown targets through pattern recognition algorithms [1]. Generally, SAR target recognition methods first perform feature extraction to obtain effective feature vectors. In [2–8], the geometric shape features were used to design SAR target recognition methods, including target regions, shadows, and contours. In [9, 10], efficient dimensionality reductions were achieved through projection algorithms such as principal component analysis (PCA) and non-negative matrix factorization (NMF). Image analysis algorithms including the wavelet, empirical mode decomposition, and monogenic signal were employed for SAR image processing with application to target recognition [11–16]. In [17–19], SAR target recognition methods based on the attribute scattering centers were developed. The application of the classifier needs to be combined with the typical characteristics of the extracted features. At this stage, most of the classifiers used in SAR target recognition came from the traditional pattern recognition field. Representative ones are K nearest neighbors (KNN) [9, 20], support vector machine (SVM) [20–23], sparse representation-based classification (SRC) [23–29] etc. In recent years, traditional neural networks have gradually moved to a deeper level, promoting the rapid development of deep learning theory. In the field of SAR target recognition, deep learning algorithms represented by convolutional neural network (CNN) have been widely used [30–41], and their effectiveness has been verified.

In this paper, the monogenic signal and Gaussian process model are jointly applied to SAR target recognition. The monogenic signal can obtain an effective feature description through multilevel time-frequency decompositions of the original SAR image, which can better reflect the target characteristics [12–15]. The Gaussian process model [42–45]
is a statistical learning algorithm based on the Bayesian framework, and all its statistical characteristics are determined by the mean and covariance functions. Therefore, the Gaussian process model is a nonparametric probability model. Compared with the traditional neural network, SVM, and other classification mechanisms, the Gaussian process model greatly reduces the parameter scale, simplifies the overall optimization process, and enhances the convergence of the model. In the application of Gaussian process model, prior knowledge can be represented as prior probability into the model, and the model’s ability to describe actual problems can be improved by flexible selection of covariance functions. And the modeling and analysis of regression or classification problems can be realized. Therefore, this paper chooses Gaussian process model as the basic classifier for SAR target recognition. First, a binary classifier is designed, and then a multiclass classifier is promoted through a one-to-one voting mechanism to meet the multiclass decision-making problem in SAR target recognition. In the specific implementation process, the feature vectors of the training and test samples are first extracted from the monogenic signal. The Gaussian process classification model is trained with the feature set of the training sample as input. For the feature vector of the sample to be identified, it is input into the trained Gaussian process model to obtain its target label. In the experiment, typical scenarios are set based on the MSTAR dataset to test the proposed method, whose performance is compared with some existing methods. The experimental results prove the effectiveness and robustness of the proposed method.

2. Feature Extraction Based on Monogenic Signal

The monogenic signal is an expansion of the analytic signal in a high-dimensional space. In particular, for image data, the two-dimensional monogenic signal can be used for characteristic analysis [12–15]. The monogenic signal is the product of the combination of the signal itself and its Riesz transform. The Riesz transformation of the signal \( f(z) \) is denoted as \( f_M(z) = f(z) - (i, j)f_R(z) \), \( i, j \) are imaginary units. \( f(z) \) and its Riesz transform correspond to the real part and imaginary part of the monogenic signal, respectively. Accordingly, the decompositions of the monogenic signal are defined as follows:

\[
A(z) = \sqrt{f(z)^2 + f_R(z)^2},
\]

\[
\varphi(z) = a \tan \left( f_R(z)/f(z) \right) \in (-\pi, \pi],
\]

\[
\theta(z) = a \tan \left( f_y(z)/f_x(z) \right) \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right).
\]

In the above equations, \( f_x(z) \) and \( f_y(z) \) correspond to the \( i \)-imaginary part and \( j \)-imaginary part of the monogenic signal, respectively; \( A(z) \) represent the amplitude information; and \( \varphi(z) \) and \( \theta(z) \) correspond to the local phase and azimuth information, respectively.

The three types of features obtained based on monogenic signal have different characteristics. Among them, \( A(z) \) mainly reflects the intensity distribution of the image. \( \varphi(z) \) and \( \theta(z) \) reflect the local detail information and shape characteristics of the image. Therefore, the joint use of the decompositions from the monogenic signal is conducive to construct more informative features.

3. Gaussian Process Model for Classification

Gaussian process model is a new kernel method developed on the basis of Bayesian neural network, which can be used to deal with classification and regression problems in machine learning. Due to its superior robustness, the Gaussian process model has been applied and verified in pattern classification and recognition problems [42–45].

3.1. Binary Classification. Generally, the Gaussian process model includes three parts: likelihood function definition, hidden variable function definition, and posterior probability calculation. The classification algorithm based on Gaussian process model uses Gaussian function to approximate the hidden variable function of the classification process. Representative methods include Laplace method, Expectation Propagation method, and Kullback-Leibler divergence minimization method.

For a training set \( D \) containing \( N \) observations, \( D = \{(x_i, y_i)\}_{i=1}^N \) where \( x_i \in \mathbb{R}^d \) is the \( i \)th input sample, \( d \) is the dimension, and its corresponding binary category label is denoted as \( y_i \) in which \( y_i = 1 \) represents the positive class, and \( y_i = -1 \) represents the negative class. \( X = \{x_1, \ldots, x_n, \ldots, x_N\} \) represents a \( N \times d \)-dimensional matrix. For the input sample \( x_i \), an implicit function \( f_i \) is defined accordingly. \( f = \{f_1, \ldots, f_N\} \) contain the implicit functions of all input samples. At the same time, with the Sigmoid function \( \rho(A) = \rho(f) = \rho(y_i = 1/f_i) \), the output of each implicit function is constrained between [0, 1]. Assuming that each sample is independent and identically distributed, their joint probability distribution can be calculated as follows:

\[
P\left(\frac{Y}{f}\right) = \prod_{i=1}^N p\left(\frac{y_i}{f_i}\right) = \prod_{i=1}^N \rho(y_i, f_i).
\]

Assuming \( f_i \) a zero mean Gaussian distribution, the prior probability \( p(f/X) \) is described as follows:

\[
p\left(\frac{f}{X}\right) = N(0, K) = \frac{1}{(2\pi)^{d/2}|K|^{1/2}} \exp\left\{-\frac{1}{2}f^TK^{-1}f\right\}.
\]

In (6), \( K \) refers to the covariance matrix of \( f \). The posterior probability of implicit function is calculated as follows:
\[ p\left( \frac{\mathbf{f}}{\mathbf{X}, \mathbf{y}, \mathbf{\theta}} \right) = \frac{p(\mathbf{y}|\mathbf{f})p(\mathbf{f}|\mathbf{X})}{p(\mathbf{y}|\mathbf{\theta})}, \]  
\[ (7) \]

where \( p(\mathbf{y}|\mathbf{f}) \) is the likelihood function and \( p(\mathbf{y}|\mathbf{X}, \mathbf{\theta}) \) represents the marginal probability. The Laplace approximation algorithm can be used to solve the posterior probability \( p(\mathbf{f}|\mathbf{X}, \mathbf{y}, \mathbf{\theta}) \) and obtain the corresponding estimated value \( q(\mathbf{f}|\mathbf{X}, \mathbf{y}, \mathbf{\theta}) \). The second-order Taylor series will be expanded at the maximum posterior probability \( \log p(\mathbf{f}|\mathbf{X}, \mathbf{y}, \mathbf{\theta}) \), and the results are as follows:

\[ q\left( \frac{\mathbf{f}}{\mathbf{X}, \mathbf{y}, \mathbf{\theta}} \right) = N(\tilde{\mathbf{f}}, A^{-1}) \exp \left( -\frac{1}{2} (\mathbf{f} - \tilde{\mathbf{f}})^T A (\mathbf{f} - \tilde{\mathbf{f}}) \right), \]
\[ (8) \]

where \( \tilde{\mathbf{f}} = \arg \max_{\mathbf{f}} p(\mathbf{f}|\mathbf{X}, \mathbf{y}, \mathbf{\theta}) \), \( A = -\nabla \nabla p(\mathbf{f}|\mathbf{X}, \mathbf{y}, \mathbf{\theta}) \) and \( \mathbf{f} \) are independent of each other, so the problem can be reorganized as follows:

\[ \varphi(\mathbf{f}) = \log p\left( \frac{\mathbf{y}}{\mathbf{f}} \right) + \log p\left( \frac{\mathbf{f}}{\mathbf{X}} \right) \]
\[ = \log p\left( \frac{\mathbf{y}}{\mathbf{f}} \right) - \frac{1}{2} \mathbf{f}^T K^{-1} \mathbf{f} - \frac{1}{2} \log |K| - \frac{L}{2} \log 2\pi. \]
\[ (9) \]

The posterior probability can be obtained as

\[ p\left( \frac{\mathbf{f}}{\mathbf{X}, \mathbf{y}, \mathbf{\theta}} \right) \approx q\left( \frac{\mathbf{f}}{\mathbf{X}, \mathbf{y}, \mathbf{\theta}} \right) \]
\[ = N(\tilde{\mathbf{f}}, A^{-1}) = N(\tilde{\mathbf{f}}, (\mathbf{W} + K^{-1})). \]
\[ (10) \]

In addition, the marginal probability distribution can be expressed as

\[ \log p\left( \frac{\mathbf{y}}{\mathbf{X}, \mathbf{\theta}} \right) = -\frac{1}{2} \mathbf{f}^T K^{-1} \mathbf{f} + \log p\left( \frac{\mathbf{y}}{\mathbf{X}} \right) - \frac{1}{2} \log |\mathbf{B}|. \]
\[ (11) \]

In Equation (11), \( |\mathbf{B}| = |\mathbf{K}| \cdot |\mathbf{K}^{-1} + \mathbf{W}| = |\mathbf{K} + \mathbf{W}^{-1}| \), \( \mathbf{\theta} \) represents hyperparameters, which can be solved by maximizing (11). For a given test sample \( \mathbf{x} \), the probability distribution of the corresponding implicit function \( \mathbf{f}_* \) is

\[ \mathbf{f}_* \sim N(\bar{\mathbf{K}}^T, \mathbf{K}_* - \mathbf{K}_*\bar{\mathbf{K}}^{-1}\bar{\mathbf{K}}^T), \]
\[ (12) \]

where \( \bar{\mathbf{K}} = \mathbf{K} + \mathbf{W}^{-1}. \) The probability of the output corresponding to \( \mathbf{y}_* = 1 \) is

\[ p(\mathbf{f}_*) = \int p(\mathbf{f}_*) p\left( \frac{\mathbf{f}_*}{\mathbf{X}, \mathbf{y}, \mathbf{x}_*} \right) d\mathbf{f}_*. \]
\[ (13) \]

According to the probability of the corresponding classes, the target label of the test sample can be determined using the binary classification.

### 3.2. Multiclass Classification

The traditional Gaussian process model can be directly used for binary classification, but practical problems often involve the discrimination of multiple classes. Therefore, it is necessary to extend the binary classification to multiple ones in order to realize the direct classification of multiple classes. Among them, a representative method of extending binary classification to multiple classifications is the one-to-one voting mechanism. This paper uses this method to extend the traditional binary classifier based on Gaussian process model for multiclass classification. The implementation process is as follows:

1. In the training stage, the training samples of class \( 1-k \) are combined in pairs to obtain \( \mathbf{C}_{ij} = k(k-1)/2 \) combinations. The Gaussian process model is used to train each combination to obtain the corresponding binary classifier \( \mathbf{C}_{ij} \), where \( i \in \{1, \ldots, k\}, j \in \{1, \ldots, k\} \).

2. In the classification stage, the target label of unknown samples is judged through the voting mechanism. First, the initial number of votes is set for each class to 0; then, the \( k(k-1)/2 \) binary classifiers which have been trained are used to classify the test samples. When the classifier \( \mathbf{C}_{ij} \) determines the \( i \)th class, the number of votes for the \( i \)th class is increased by 1. If the classifier \( \mathbf{C}_{ij} \) judges the test sample to be the \( j \)th class, the number of votes for the \( j \)th class is increased by 1. Finally, the total number of votes obtained for each class is counted, and the category with the highest number of votes is judged to be the target label of the test sample.

In this paper, the binary classification mechanism of the Gaussian process model is combined with the one-to-one voting mechanism to obtain a multiclass classifier.

### 3.3. Target Recognition Procedure

In this paper, the monogenic signal and Gaussian process model are applied to SAR target recognition, which are used for feature extraction and classification, respectively. Figure 1 briefly shows the basic process of the proposed method. The main body is divided into two stages: training and testing. The main implementation steps are summarized as follows:

**Step 1:** The monogenic signal is used to perform feature extraction on all training samples.

**Step 2:** The monogenic feature vectors of the training sample are used as inputs and the corresponding target labels as output to train a multiclass Gaussian classification model.

**Step 3:** The monogenic signal is used to perform feature extraction on the test sample to be classified.

**Step 4:** The monogenic feature vector of the test sample is input into the Gaussian process model after training, and the posterior probability of each class is calculated.

**Step 5:** The target label of the test sample is determined according to the principle of the largest number of votes.

Compared with the traditional SAR target recognition methods, the proposed one introduces Gaussian process
model, which provides a statistical way for decision. Therefore, it can obtain the optimal decision in the sense of probability. By combining the decision criteria of the maximum posterior probability and the maximum number of votes, it is helpful to obtain more reliable target recognition results.

4. Experiments

4.1. Description of the Dataset. The MSTAR dataset is employed to set up typical test scenarios to carry out experiments and verification. The appearances of the targets included in the dataset are shown in Figure 2.

Some existing SAR target recognition methods are selected in the comparison algorithms, including NMF [10], Mono [12], BEMD [16], and ESENet [136]. These four types of reference methods basically cover the most commonly used features and classifiers in existing SAR target recognition. In the subsequent experiments, three experimental scenarios are set to investigate the proposed method, namely: Scenario 1: standard operating condition, involving 10 types of targets, Scenario 2: depression angle differences, involving 3 types of targets, and Scenario 3: noise corruption, involving 10 types of targets.

4.2. Results and Discussion

4.2.1. Scenario 1. Table 1 gives a description of the standard operating condition in Scenario 1, including 10 types of targets. The training set uses SAR images at 17° depression angle, and the classifier is obtained to test the samples at 15° depression angle. The comparison shows that the target configurations between the two sets remain the same, with only a 2° depression angle difference, so their overall correlation is strong. Figure 3 shows the results of the proposed method in the current scenario, the single-class recognition rate is higher than 98.5% (shown in diagonal elements), and the average recognition rate of 10 classes reaches 99.32%, which reflects the effectiveness of the proposed method. The average recognition rates of various methods under Scenario 1 are shown in Table 2. The recognition rates of NMF, monogenic signal, BEMD, and ESENet methods are 98.26%, 98.69%, 99.02%, and 99.12%, respectively, which are all higher than 98%. It can be seen that the recognition problem under the standard operating condition is relatively simple.

By comparing the average recognition rates of various methods, it can be seen that the method in this paper has some performance advantages. The recognition rate of the ESENet method under the current condition is second only to the proposed method, which benefits from the classification ability of the deep learning model. In this paper, the discriminative features of the target in the SAR image are obtained through the monogenic signal, and the statistically optimal classification model is obtained by introducing the Gaussian process model, which effectively improves the target recognition performance under the standard operating condition.

4.2.2. Scenario 2. The extended operating condition refers to the large differences between the test sample and the training sample due to the changes in the SAR data acquisition conditions. Typically, the extended operating conditions in SAR target recognition include target configuration differences, depression angle differences, and noise corruption. In this experiment, the proposed method is tested under the condition of different depression angles, and Scenario 2 shown in Table 3 is set. Among them, the samples at 17° depression angle are used for training; the samples at 30°, and 45° depression angle are used for classification, which shows that there are large depression angle differences between the training and test samples. Different methods are examined on the two test sets, and the recognition results are obtained as shown in Figure 4. Comparing the results at the two depression angles, the overall performance at 30° is significantly better than 45°, indicating that large depression angle differences will lead to greater image differences. From the results at the two depression angles, the method in this paper has achieved the highest average recognition rate, showing its better robustness. The monogenic signal can better analyze the relevant characteristics of the SAR images. The Gaussian process model can more effectively explore the internal correlation between the real target labels by deriving the best statistical model, so the robustness of the recognition method to the depression angle difference can be improved.

4.2.3. Scenario 3. Noise corruption is another typical extended operating condition, mainly because the signal-to-noise ratio (SNR) of the SAR image to be identified is
relatively low, resulting in a large difference from the training sample. Based on the test and training samples in Table 1, different degrees of noises are added to the test samples, so as to construct test sets with multiple SNRs in Scenario 3. Specifically, according to the test sample's own energy, the additive Gaussian noise is obtained according to the preset SNR, and it is mixed into the original test sample to obtain the noisy test sample corresponding to the noise level. Then, various methods are tested at each noise level, and the recognition results shown in Figure 5 are obtained. It can be seen that as the noise level continues to decrease, the average recognition rates of various methods show clear downward trends. The comparison shows that the method in this paper achieves the highest recognition rate at each noise level.
In this paper, the monogenic signal and Gaussian process model are applied to SAR image target recognition. The Gaussian process model constructs a Bayesian learning model by combining the kernel function and probability discrimination to obtain the best regression model in the statistical sense. The monogenic feature vector of the SAR image is used as the input, and the target label is the output. The regression mapping relationship between the two is constructed, so as to obtain a robust classification model. Based on the MSTAR dataset, three typical scenarios are set to test the proposed method and compared with the existing methods. The experimental results are as follows: In Scenario 1, i.e., the standard operating condition, the average recognition rate of the proposed method for 10 types of targets reaches 99.28%, which is higher than the four types of reference methods, verifying its effectiveness for multiclass target recognition problems under the standard operating condition. Under the condition of Scenario 2, i.e., depression angle differences, the average recognition rate of the proposed method for the test set at 30° and 45° depression angles is 98.04% and 73.13%, respectively, which is higher than the reference methods, verifying its robustness to the depression angle difference. In Scenario 3, i.e., noise corruption conditions, the proposed method maintains the highest average recognition rate under each noise level, showing its noise robustness.

**Data Availability**

The dataset can be accessed upon request.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**References**


