Radar Signal Classification Based on Bayesian Optimized Support-vector Machine

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Abstract. Radar uses the scattering of electromagnetic waves to identify target coordinates and provide detection information. It plays a vital role in modern production and military affairs. How to classify and recognize radar signals is one of the main problems in current researches. With the emergence of various new radars, the demand for high accuracy in radar classification technology is gradually increasing. Furthermore, traditional signal classification methods cannot achieve good results. Aiming at the problems of low accuracy and poor performance of traditional classification methods, this paper proposes a radar signal classification technology based on Bayesian Optimized Support Vector Machines. The principle of the method is analyzed, and simulation data sets verify the theory. Moreover, the proposed method was compared with the traditional SVM, and the accuracy is increased by 10.71%.

Keywords: Bayesian optimization, vector machine, radar classification.

1. Introduction
The classification of radar signals is one of the core technologies of radar signal processing. With the continuous development of modern electronic technology, various new radars with complex signal characteristics have emerged. Due to the increasingly complex electromagnetic environment and crowded signal spectrum, the performance of traditional radar identification and classification methods continues to decline, which can no longer meet the increasing demand for high precision. In addition, there are various external interferences in application scenarios such as battlefields, which causes specific difficulties for accurate classification and recognition.

Radar classification methods based on artificial intelligence mainly include decision tree, Support Vector Machine (SVM), K-nearest neighbor algorithm (KNN), and so on [1]. The decision tree is a tree structure model that classifies samples based on features. It is proposed an improved decision tree algorithm, which uses parallel programs and efficiently processes a large amount of data [2]. However, as a linear model, the decision tree can not extract the complex radar signal features. KNN algorithm gets the prediction result by calculating the nearest sample to the input sample [3], but KNN needs to
occupy a large amount of storage space to store known examples, which affects the recognition efficiency [4].

In recent years, SVM has been widely used in the field of classification. The limited data information seeks the best compromise between its penalty ability of the error and its control ability of overfitting and finally obtains the excellent generalization ability. Furthermore, Bayesian optimization finds the value that minimizes the objective function by establishing a substitution function (probability model) based on the objective function's past evaluation results.

The paper proposes a radar classification framework based on Bayesian Optimized SVM (BO-SVM) to effectively solve the classification problem under the problematic interference of radar signals. The experimental data shows that compared with the traditional SVM model, BO-SVM classification accuracy is much improved, indicating that the model can be applied to radar signal classification to improve the classification accuracy and efficiency and has a broad prospect of application.

2. Radar Classification Based on Bayesian Optimized Support Vector Machine

2.1. SVM algorithm

SVM classifier is the simplest and most effective method to solve the problem of non-linear sample data classification. SVM classification method has good generalization ability.

SVM solves the classification problem by minimizing the structural risk and constructing a hyperplane to separate the two data types by the most considerable distance. Among the data samples of SVM, two types of samples are considered to be linearly separable: \((x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l)\), \(x \in \mathbb{R}^n, y \in \{-1, +1\}\). When the distance between the two types of sample points and this hyperplane is the largest, this plane is called the optimal hyperplane, as shown by \(H\) in Figure 1.

![Figure 1. The SVM Schematic diagram.](image)

SVM classification process:

\[
(1) \quad \sum_{i=1}^{l} y_i a_i = 0, a_i \geq 0 \quad (a_i \text{ is the Lagrangian factor}): \text{Obtain the maximum value } a_i \text{ by Lagrangian method } (a_i^* \neq 0, \text{Corresponds to the support vector}).
\]

\[
W(\alpha) = \sum_{i=1}^{l} a_i - \frac{1}{2} \sum_{i=1}^{l} a_i a_j y_i y_j (x_i \cdot x_j)
\]
(2) $W^*$ and $b^*$ are derived from the following formula, where $x_i$ is a special support-vector.

$$W^* = \sum_{i=1}^{t} \alpha_i^* y_i x_i, b^* = \frac{1}{y} - W^* \cdot x_i$$

(3) Use the kernel function to classify the vector and get the optimal classification function.

$$D(x) = \text{sgn}(\langle w^* \cdot x \rangle - b^*) = \text{sgn}\left(\sum_{i,j=1}^{t} \alpha_i^* y_i \langle x_i \cdot x \rangle - b^*\right)$$

2.2. Bayesian optimization theory

Bayesian Optimization (BO) comprehensively weighs the search and utilization of the sample space. It uses prior information and observation results to control the posterior distribution of the function space and quickly seeks the optimal solution through the collection function's guidance. BO is regarded as a global optimization method. And the optimization principle follows the maximum expected utility or equivalent expression of the minimum expected risk, which is very suitable for functional processes with no closed-form and high running cost.

The probabilistic agent model and acquisition function are important components of BO. Probabilistic proxy models can be divided into parametric models and non-parametric models. The non-parametric models have high scalability, so they are widely used. The acquisition function refers to the function mapped from the input, observation, and hyperparameter space to the real number space.

Bayesian theory is the core of Bayesian optimization theory. The primary expression of Bayesian theory is

$$p(\theta|x) = \frac{p(\theta)p(x|\theta)}{p(x)}$$

Where $x$ represents the observation data, $\theta$ represents the parameter set in the model, $p(\theta)$ represents the prior information of the parameter, $p(x|\theta)$ represents the likelihood function, $p(\theta|x)$ represents the posterior information of the parameter, and $p(x)$ can be expressed as follows

$$p(x) = \int p(\theta)p(x|\theta)d\theta$$

From equation (5), we know that $p(x)$ and $\theta$ have nothing to do, so equation (4) can be simplified, and the basic expression of Bayesian theory is

$$p(\theta|x) \propto p(\theta)p(x|\theta)$$

2.3. Radar Classification Framework Based on Bayesian Optimized Support Vector Machine

The critical parameters of SVM are kernel function parameter $g$ and penalty factor $C$, which have a great influence on the classification accuracy of SVM. The SVM parameters $C$ and $g$ can be automatically optimized by the Bayesian algorithm.

The execution flow chart of the proposed radar classification framework based on Bayesian Optimized Support Vector Machine is shown in figure 2.
3. Example Analysis

3.1. Radar signal acquisition
This paper uses MATLAB simulation to generate three kinds of radar signals: rectangular, linear frequency modulation (LFM), Barker code. Furthermore, each kind has 3000 samples. For each sample, the pulse width and repetition rate will be generated randomly, so even radar signals belonging to the same category are different, which increases the difficulty of classification. Among them, the scanning bandwidth and direction of the LFM waveform are randomly generated, and the chip width and number of the Buck waveform are also randomly generated. To simulate a more
complex environment, for different types of radar signals generated by simulation, Gaussian white noise is added with a random signal-to-noise ratio in the range of [-6, 30] dB to make it more in line with the actual situation. The random carrier frequency is offset within the range of [Fs/6, Fs/5] on each signal, and each signal passes through the multipath attenuation channel. The spectrograms of the three signals are shown in Figure 3.

![Figure 3. The spectrum of the three radar signals.](image)

### 3.2. Radar Classification Results Based on Bayesian Optimized Support Vector Machine

This paper uses 5-fold cross-validation to evaluate the classification performance of the model. The 5-fold cross-validation performs arithmetic average on the results of 5 iterations and calculates the model's average classification accuracy under this parameter combination, and the evaluation result is reliable. Due to the high flexibility, scalability, and analysis of the Gaussian process, the Gaussian process is used as a probabilistic proxy model in the experiment. Through the radar mentioned above signal data, the BO-SVM classification framework was trained and verified. A total of 30 iterations were performed, and parameter settings of the model are shown in Table 1.

| Parameters                  | Settings                          |
|-----------------------------|-----------------------------------|
| Multi-class methods         | 1 to 1                            |
| Kernel function             | Gaussian                          |
| Acquisition function        | Expected improvement per second (plus) |
| Number of iterations        | 30                                |
| Standardized data           | true                              |

#### Table 2. Radar classification results based on Bayesian optimization SVM.

| Parameters                      | Results         |
|---------------------------------|-----------------|
| Accuracy                        | 93.0%           |
| Total misclassification costs   | 634             |
| Prediction speed                | ~3900 obs/sec   |
| Training time                   | 16223s          |
| Box constraint level            | 996.1668        |
| Nuclear scale                   | 62.146          |

The results are shown in Table 2. According to Table 2, the accuracy of BO-SVM classification can reach 93.0%. The confusion matrix is shown in figure 4.
3.3. Comparison and verification of different algorithms

3.3.1. Comparison between the proposed method and the traditional SVM algorithm. This paper also uses a traditional linear SVM algorithm to classify the same radar signals for comparison and verification. The specific parameter settings are the same as the BO-SVM algorithm. The results are shown in Table 3. It can be seen that the accuracy of the BO-SVM classification algorithm is 10.71% higher than that of the traditional SVM. Meanwhile, it is found that the BO-SVM algorithm has a longer training time, slower prediction speed, and higher requirements for computer configuration. It is a problem that needs further research and improvement in the future.

![Radar classification confusion matrix based on BO-SVM algorithm.](image)

**Table 3.** Radar classification results based on linear SVM algorithm.

| Parameters                     | Results          |
|-------------------------------|------------------|
| Accuracy                      | 84.0%            |
| Total misclassification costs | 1437             |
| Prediction speed              | ~143000 obs/sec |
| Training time                 | 107.53 seconds   |

3.3.2. Comparison with Other Algorithms. To further verify the Bayesian optimization SVM algorithm's effectiveness, the paper uses the Gaussian Naive Bayes algorithm, decision tree, and linear discriminant analysis to classify the obtained radar signals. The three methods' parameter settings are shown in Table 4, and the classification results are compared with the classification results of BO-SVM in Table 5.
Table 4. Parameter Settings for Three Algorithms.

| Algorithm name            | Parameters                          | Settings             |
|---------------------------|-------------------------------------|----------------------|
| Bayesian                  | Name of numerical forecast variable distribution | Gaussian          |
|                           | Maximum number of splits            | 100                  |
| linear discriminant analysis | Secession guidelines              | Gini Diversity Index |
|                           | Alternative decision-making split    | Closed               |
| linear discriminant analysis | Covariance Structure              | Full                 |

Table 5. Comparison of classification results of three algorithms with those of Bayesian optimization SVM algorithms.

| Algorithm name            | Accuracy | General error Cost | Forecast speed (obs/sec) | Duration of training (s) |
|---------------------------|----------|--------------------|--------------------------|--------------------------|
| BO-SVM                    | 93.0%    | 634                | ~3900                    | 16223                    |
| Bayesian                  | 68.3%    | 2855               | ~12000                   | 15.874                   |
| decision tree             | 85.3%    | 1324               | ~14000                   | 24.924                   |
| linear discriminant analysis | 79.4%    | 1856               | ~5400                    | 18.925                   |

According to the comparative analysis of experimental results, the accuracy of the BO-SVM algorithm's classification results is higher than that of the other three classification algorithms in the experiment, which is 19.74% higher on average.

4. Conclusion

Aiming at the problem of poor radar signal classification under noise conditions, this paper proposes a Bayesian optimized support-vector machine radar classification method. Based on simulation data, the classification accuracy of the proposed method can finally reach 93.0%, which is 10.71% higher than the traditional linear SVM algorithm and 19.74% higher than the other three classification algorithms on average, indicating that the method has a high classification accuracy and a broad prospect in the application.

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