An Echo Sequence Profile Image Based Ship Target Classification Algorithm for Low-Resolution Radar

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Abstract. Ship target classification is of great significance in both military and civilian fields. We propose a ship target classification algorithm for low-resolution radars with echo sequence profile images. This algorithm can be realized in the following steps. First, we collect radar profile image data. We use five perspectives of a radar target, including target shape, Radar Cross Section (RCS), echo amplitude, motion attribute, and features of two-dimensional grayscale maps, to extract eight-dimensional feature vectors. The proposed algorithm uses the Support Vector Machine (SVM) as the classifier, and the parameters of the classifier are optimized by either grid search or the Particle Swarm Optimization (PSO) algorithm. The proposed algorithm is verified through real data classification tests.

Keywords: Low-resolution radar, target classification, feature extraction, support vector machine.

1. Introduction

Radar Automatic Target Recognition (RATR) is a technique to achieve automatic determination of target attributes, types, or categories by extracting target features based on radar echo sequences. It is found that most of the existing radars are narrow-band and low-resolution radars, which cannot provide enough information to make accurate recognition on target types [1]. Low-resolution radar is characterized by wider pulse width, narrower bandwidth, and poor radial range resolution [2]. Compared with the one-dimensional echo sequence, the two-dimensional profile image consists of both distance and azimuth, which not only provides the echo amplitude information but also reflects its correlation information with azimuth angle. Therefore, two-dimensional radar profile images are commonly used for low-resolution radar target recognition.

The selection of features with high separability and stability plays a crucial role in the classification capability. [3] classified ship targets with different working conditions based on Radar Cross Section (RCS). [4] combined three different methods to classify island targets and ship targets using waving values of target profile images. [5] and [6] used RCS and spectral entropy to tri-chotomize ground targets for tri-classification. [7] used five-dimensional feature vectors such as central moments and skewness of two-dimensional profile images for tri-classification of ship targets. Numerous studies have shown that extracting more features to form feature vectors usually leads to higher classification accuracy. Moreover, the commonly used methods include the k-Nearest Neighbor (kNN) algorithm [8], the Support Vector Machine (SVM) algorithm [8,9], the neural network [2], or a combination of them [10]. Among them, SVM has a simple structure with better generalization ability in small data set training.
In order to overcome the problems of the poor radial resolution, feature aliasing of low-resolution radar, and improve the recognition accuracy, we propose a complete ship target classification algorithm via echo sequence profile images for low-resolution radar. First, we collect radar profile image data and construct data set. Five perspectives of radar, including target shape, Radar Cross Section (RCS), echo amplitude, motion attribute, and features of two-dimensional grayscale maps, are used to extract eight-dimensional feature vectors. Finally, we use SVM to recognize and classify the targets. The experiments on real data prove the effectiveness of the algorithm.

2. Principle of Radar Echo Sequence Profile Image
The radar beam scanning process is shown in figure 1. The radar target echo sequence profile image is a two-dimensional image formed by arranging the echo sequences during the scanning process in azimuthal order and then projecting them to azimuth and distance. The projection width of the echo sequence in azimuth and distance is called azimuthal broadening and distance broadening, respectively.

![Figure 1. Radar beam scanning.](image_url)

Compared with the target recognition method that uses one-dimensional echo sequences [2, 9], the target recognition method based on two-dimensional profile images can not only provide echo amplitude information but also reflect the correlation information between echo sequences and azimuths. Thus, profile images provides favourable auxiliary information for target classification.

3. Principle of Radar Echo Sequence Profile Image
The selection of features or feature vectors with high separability and stability plays a crucial role in the classification ability. In this paper, eight features are extracted from five perspectives for target recognition. The eight features are illustrated as follows.

3.1. Shape Features
The target shape is the most basic feature of the profile image. In this paper, we use area (number of non-zero echo points) and lateral length as the first feature and the second feature to characterize the target shape, which can be given respectively as

\[ f_1 = \sum_i \{y_i \neq 0\} \]  
\[ f_2 = \theta_i R \]

where, \( y_i \) denotes the size of the \( i \)-th echo value, \( \theta_i \) is the broadening caused by the lateral length of the target, and \( R \) denotes the distance between the target and the radar.

3.2. RCS Feature
Let the radar cross-sectional area of the target be \( \sigma \), the echo power \( P_r \) received by the radar satisfies

\[ P_r = \frac{P_t G A_e \sigma}{(4\pi)^2 R^4} = \frac{1}{k} \frac{\sigma}{R^4} \]  

where, \( P_t \) is the radar transmit power, \( A_e \) is the effective receiving area of the antenna, \( G \) is the antenna gain, \( R \) is the distance between the target and the radar, and \( k \) is a constant. From (3), it can be derived that the target intercept area, \( \sigma \), is
\[ \sigma = kP, R^4 \] (4)

Therefore, the third feature of this paper is chosen as
\[ f_3 = 10 \log_{10} \left( P, R^4 \right) \] (5)

3.3. Echo Amplitude

Under normal conditions, the echo amplitude peak of a large ship is larger than that of a small ship when the distance is the same. The fourth feature used in this paper is
\[ f_4 = \max \{ y_i \} \] (6)

3.4. Motion Attribute

The speed is the main motion attribute of a ship target and the measurement of the target velocity is directly achievable by in-service radars. The fifth feature used in this paper is defined as
\[ f_5 = v \] (7)

where \( v \) is the target velocity.

3.5. Features of Two-dimensional Grayscale Maps

The profile images can be processed as general two-dimensional grayscale maps after normalization and image size complementation. Denote by \( H(i, j) \) the pixel value of the \( i \)-th row and \( j \)-th column of the grayscale image, the sixth feature used in this paper is the image energy, which is given as
\[ f_6 = \sum_{i,j} H^2(i, j) \] (8)

Let \((x, y)\) be the coordinate of an object point represented by the image and \((x_c, y_c)\) be the centre of the object, then the \( p + q \) order central moment is given as
\[ \mu_{p,q} = \sum_{(x,y) \in R} (x - x_c)^p (y - y_c)^q \] (9)

By normalizing these central moments, seven invariant moments can be obtained [11]. The seventh and the eighth features are the first two invariant moments, which can be given respectively as
\[ f_7 = \mu_{2,0} + \mu_{0,2} \] (10)
\[ f_8 = (\mu_{2,0} - \mu_{0,2})^2 + 4\mu_{1,1}^2 \] (11)

4. Ship Target Recognition Process Based on Eight Features and SVM

The steps of ship target recognition in this paper are shown in figure 2.

![Figure 2. Ship target identification steps.](image)

For classifier training, we firstly collected the data of radar echo sequences from an available radar station. The data set is constructed based on the echo data and Automatic Identification System (AIS)
messages. Then, eight features are extracted to form a feature vector set. After that, the feature vectors are normalized, and the normalized parameters are saved. Finally, the SVM classifier is optimized and trained based on the normalized feature vector set and the trained model is saved.

For ship target recognition, the target data of the ship to be measured are collected firstly. Then, eight features are extracted to form a feature vector and normalized by the saved normalization parameters. After that, the trained SVM classifier is used to classify the ship.

In this paper, we collect radar data from 3-12 kilometres and classify ships into seven categories by length. The training and test sets are divided by 8:2. The data set construction and optimization methods of SVM parameters are introduced in Sections 4.1 and 4.2, respectively.

4.1. Data Set Construction

The process of radar target data set construction is: using the C-band radar that has been set up, the data collector is activated to record the radar echo data. At the same time, the AIS message acquires the target position, motion status, target type, and other information. The original data is stored in a DAT file. The data format is shown in figure 3, where the first 42 bytes are information data, including Maritime Mobile Service Identify (MMSI), start/end position, start/end distance, echo data quantity, and so on. Echo data consists of echo sequences of m azimuths, each azimuth has n data by distance, arranged in the format of “bearing (2 bytes) + echo sequence (n bytes)”.

![Figure 3. Data acquisition format.](image)

Based on the unique MMSI number of each ship, information such as the length and the type of the ship can be obtained. The echo sequences are arranged by azimuth to obtain two-dimensional echo sequence profile image data. Figure 4 gives an example of a two-dimensional echo sequence profile image. In this paper, the raw data are grouped by MMSI number as training and testing data sets.

![Figure 4. An echo sequence profile image (ship length=165m, distance=8km).](image)

4.2. Classifier Parameter Optimization

Due to the advantages in generalizability and complexity, a Radial Basis Function (RBF) based SVM classifier is used. The parameters to be optimized are the penalty factor $C$ and the RBF kernel parameter $\gamma$. We use grid search and PSO to optimize the parameters and make performance comparison.

4.2.1. Grid search. The process of grid search has the following steps. First, we set up the parameter grid, where each point represents a parameter combination. Then, the score for each combination is obtained in turn by enumeration. Finally, the parameter combination with the highest score is outputted. The advantage of the grid search is that the structure is simple and the search is comprehensive while the disadvantage is that the accuracy is limited by the grid interval and each optimization must search all the grid points, which makes it lack flexibility.

4.2.2. PSO algorithm. The PSO algorithm was proposed by J. Kennedy and R. C. Eberhart in 1995. The basic principle is to iterate from a number of random positions to find the individual optimum and the global optimum. The advantages of the PSO algorithm are high accuracy and fast convergence while the disadvantage is that it is easy to fall into the local optimum.
The velocity vector and position vector of the \(i\)-th particle are represented by \(V_i\) and \(X_i\), respectively, and the \((t+1)\)-th iteration is formulated by (12) and (13)

\[
V_i(t+1) = \omega V_i(t) + c_1 r_1 (P_{ib}(t) - X_i(t)) + c_2 r_2 (G_b(t) - X_i(t))
\]

\[
X_i(t+1) = X_i(t) + V_i(t+1)
\]

where \(\omega\) is the inertia weight, \(c_1\) and \(c_2\) are the learning factors, \(r_1\) and \(r_2\) are uniformly distributed random numbers in the range of 0 to 1, \(P_{ib}\) is the individual optimal position of the \(i\)-th particle, and \(G_b\) is the global optimal position.

We use the accuracy of the cross-validation as the fitness of particles.

5. Experiment with Real Data

5.1. Scene Parameters

In this paper, narrowband low-resolution radar operating on C-band is used to identify ship targets longer than 15m in 3-12 kilometres of sea area. The radar parameters are shown in table 1. The classification rules and corresponding data size are shown in table 2.

Table 1. Radar parameters.

| Technical specifications               | Parameters |
|---------------------------------------|------------|
| Operating frequency band              | C-band     |
| Operating frequency range             | 4-8GHz     |
| Measurement range                     | 0.05km-105km |
| Scanning bandwidth                    | 4MHz       |
| Distance Resolution                   | 37.5m      |
| Sampling frequency                    | 10MHz      |
| Distance unit                         | 15m        |

Table 2. Classification parameters.

| Category                   | Category | Category | Category | Category | Category | Category | Category |
|----------------------------|----------|----------|----------|----------|----------|----------|----------|
| Ship                       | \(\leq 30\) | 30-60    | 60-100   | 100-140  | 140-170  | 170-200  | >200     |
| Data Size/pc               | 394      | 324      | 1059     | 3832     | 1512     | 2675     | 549      |

5.2. Effect of Different Feature Combinations

By combining different features to compose multidimensional feature vectors, a multi-angle reflection of features of the target can be achieved. The combination of features used in existing studies is usually single in type or small in number, which makes it difficult to achieve good results when the number of classification categories is much larger. In this paper, eight-dimensional feature vectors of area, lateral length, RCS, echo amplitude peak, velocity, image energy, Hu1, and Hu2 are used for target recognition. The feature combinations proposed in this paper are compared with some of the feature combinations used in other existing works of literature (see table 3). Combination 1 is the three-dimensional feature vector of lateral length, RCS, and echo amplitude peak proposed in [12]. Combination 2 is the five-dimensional feature vector of the central moment, skewness, energy, entropy, and Hu2 used in [7].

Table 3. Classification accuracy with different feature combinations.

| Features         | Combination 1 | Combination 2 | Combination 3 (proposed) |
|------------------|---------------|---------------|--------------------------|
| Accuracy         | 51.04%        | 52.73%        | 90.48%                   |

Combination 1 uses a small number of features and combination 2 uses the grayscale image characteristics without considering typical radar features such as RCS. Thus, in the classification of seven categories by length, both of them have low accuracy. The eight-dimensional feature combination proposed in this paper has the highest accuracy of 90.48%.
5.3. Effect of Different Parameter Optimization Algorithms

By default, SVM classifier parameters are usually set to $\gamma = 1/N$, $C = 1$, where $N$ is the number of classification categories. In this paper, parameter optimization is performed in two ways: grid search and PSO. For grid search, we set the grid to be $\log(\gamma) \in \{-3,-2.5,-2,-1.5,-1,-0.5,0,0.5,1,1.5,2\}$, $\log(C) \in \{0,1,2,3,4,5\}$. For the PSO algorithm, the maximum number of iterations is set to be 40.

From Table 4, it can be proved that when using the SVM classifier, the classification accuracy is largely affected by the classifier parameters. The recognition accuracy after optimizing the parameters with either PSO or grid search is improved by more than 20% compared with before. With similar optimization time, using PSO may obtain slightly higher accuracy than grid search.

| Method               | No optimization | Grid Search | PSO algorithm |
|----------------------|-----------------|-------------|---------------|
| Accuracy             | 69.00%          | 89.27%      | 90.48%        |

6. Conclusion

In this paper, a ship target classification algorithm based on echo sequence profile image and SVM classifier was proposed for low-resolution radar. The effectiveness of the algorithm was verified by real data. Meanwhile, the importance of the optimization of SVM classifier parameters on the recognition accuracy was verified. The PSO algorithm led to the highest accuracy, slightly higher than the method of the grid search, and much larger than using default parameters.

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