2012 4th International Conference on Signal Processing Systems (ICSPS 2012)
IPCSIT vol. 58 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.V58.19

Recognition of Two Types of Air-Targets with KNN-SVM Method

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Abstract. The differences in spectrum structures of the helicopters and fixed-wing aircraft are analyzed in this paper, when Doppler spectrum measurement ability cannot be met. A kind of KNN (k nearest)-SVM (support vector machine)-based air subjects recognition method is proposed. KNN is used to screen the to-be-trained spectrum samples of the helicopters to ensure the possibility of obtaining the optima distinction which reflects the characteristics of the spectrum structures of the two research subjects. Accumulation method is used to solve the problem of the recognition of the helicopter spectrum samples that are similar to the fixed-wing aircraft ones and the corresponding accumulated strategies are presented. And the results of the experiment by raw data indicate that the method employed is effective.

Keywords: target recogition, doppler specrum measurement ability, K nearest, support vector machine, accumulated.

1. Introduction

For the reason that the helicopters are quite different from the aircrafts with fixed wings in the intimidatory effects and destructive results, to detect and accurately identify the two types of aircraft targets is necessary. The recognition of these two types of air targets for radar is mainly based on the characteristics of the echoes coming back from the main gyro-wings. Due to the modulation of the rotation of the gyro-wings, the modulated echoes shows as $\sin c$ function in time domain and its instantaneous frequency spectrum will be broadened. As a result, the frequency spectrum of echoes is different in shapes between the helicopter and the aircrafts with fixed wings on which we can make the recognition.

Support vector machine (SVM) is a new machine learning method proposed by Vapnik and his research team AT & T Bell Labs [1], [2]. It builds on the principle of the minimum structural risk and has the advantages in learning ability and generalization performance which are effective to solve the small sample size, high dimension, nonlinear problems, local minima and other practical problems. Thus SVM provides a new potential approach for radar target recognition [3-5]. This article will apply the method to the air targets recognition and is quite significant in practice.

However, when applying SVM to the air target recognition directly some problems come forth. To extract the feature that the gyro-wings echoes broaden in frequency spectrum, we need receive echoes which are as large as possible. That is to say longer beam resident interval and higher pulse repetition frequency (PRF) are required for the radar [6], [7]. However, in practice, it's hard to meet the requirements above, resulting we may not get the broadening spectrum and other information in observations. In the case that the radar can't catch the spectrum broadening, the helicopter spectrum demonstrated the same figure with the fixed-wings aircraft. And then a training set including the samples of this type of helicopters frequency spectrum consistent, it will be impossible to obtain the optimal separating surface which can reflects the spectral characteristics in the two types of air targets [13-15].

This paper proposed a KNN-SVM-based air target recognition algorithm. First, the spectrums of helicopter training sample sets were screened using KNN algorithm to weed out the helicopter spectrum samples which is

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similar with the fixed-wings samples'. And then the fixed-wings spectrum samples sample and the left helicopter training spectrum samples will be the training with SVM to ensure the possibility of obtaining the optimal separating surface which can reflects the spectral characteristics in the two types of air targets. Secondly, in order to improve the recognition rate of the helicopter spectrum samples which is similar with the fixed-wings samples, we proposed a method for processing through the accumulation and the corresponding accumulation strategies. Experimental results show that, compared with the direct use of SVM training, the proposed method improved the recognition rate to a certain extent and the accumulation strategy ensure the stability of the recognition results.

2. Analysis of Air Tagets Characteristic

When electromagnetic waves irradiate rotation blades, as long as the radar beam irradiation time is long enough, the radar receiver can detect a series of echo pulses. When electromagnetic waves irradiate rotation blades perpendicularity, the returns are strongest, thus the so-called echoes "flash" forms. The flash is given by $\sin c$ function, the width of the main lobe the flash pulse duration) is as follows:

$$\Delta T = \frac{k\lambda}{4\pi f_{rot}(l-r)} \quad (1)$$

Where λ is the radar wavelength, f_{rot} is the rotation velocity, l is the length of blades, r is the shaft radius. When the blade number N is odd, $k=2$, when the blade number N is even, $k=1$.

In order to obtain sampling opportunities in the flash pulse duration and detect the targets effectively and reliably, the radar pulse repetition frequency will be limited:

$$PRF \geq \frac{1}{0.443\Delta T} \quad (2)$$

To avoid sample loss, usually we need sample twice at least within a flash pulse which is possible to meet the for large PRF. but if PRF is small, the flash pulse isn't sampled so and the Doppler spectrum obtained can't show the target characteristics. Therefore, in recognition on helicopters and fixed-wings aircrafts, we should choose the appropriate PRF in the conditions of determined wavelength of the radar.

Flash pulse interval is:

$$T_p = \frac{1}{kNf_{rot}} \quad (3)$$

Obviously, the longer beam resident interval help we get more flash pulses and detect the gyro-wings signals. The typical value of rotation speed f_{rot} generally corresponds to $5 \sim 5.8Hz$ and the maximum possible flash pulse interval is 50ms, thus the radar requires a wide beam width and a show rotation velocity of antennas to get the beam resident interval longer than 50ms, and at least one chance to detect flash pulses. If the detection capability need to be improved further, the longer beam resident interval is required.

The recognition of these two types of air targets for radar is mainly based on the characteristics of the echoes coming back from the main gyro-wings. Whether we can get the figures of gyro-wings echoes is decided by the ability of Doppler spectrum measurements for radar. That is to say the radar requires long beam resident interval and high PRF. In the case that the ability of Doppler measurement is met, under ideal conditions the Doppler spectrum of helicopters and fixed wings aircrafts are shown in Figure 1 and Figure 2.

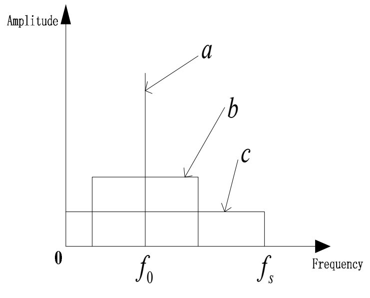

Fig.1: Ideal structure of helicopter spectrum

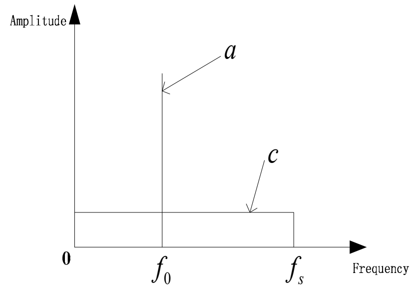

Fig.2: Ideal structure of fixed-win spectrum

From Fig. 1 and Fig. 2 , f_s is the sample frequency, a is the single frequency located at f_0 which is generated by the body with a radial velocity V, and the Doppler spectrum of helicopters and fixed wing aircraft both contain this frequency components. C is the noise component generated by the radar receiver is uniformly distributed. B is the wide Doppler spectrum generated by gyro-wings echoes due to modulation of gyro-wings to radar signals and this modulation is unique for helicopters. Clearly, whether there exist b is the main difference between the Doppler spectrum of helicopters and fixed wings aircrafts. In the case that the capability of Doppler measurement is not met, we can't catch the information of modulation of gyro-wings due to the incomplete observation. As a result part of the Doppler spectrums of helicopters and fixed-wings aircrafts are exactly the same.

3. KNN-SVM Algorithm

SVM classifier can solve the optimal classifier design problem [8], [9], providing a potential new approach to solve practical problem of radar target recognition [10]. However, SVM applied directly to the air target recognition may be some problems. Doppler measurement capability in the conditions are not met, some helicopters and fixed-wing aircraft Doppler structure identical structure. At this point the spectrum will contain data such helicopter training samples using SVM for training, it is difficult to get he optimal classification surface of the air targets. In many cases, trying to use a complex model of limited training samples will have a decreased ability to promote [9].

In fact, not having rotor modulation spectrum affects the direction of the optimal classification surfaces and the speed of the classifier training. Therefore, if this part of the training data prior to be deleted, it is possible to get optimal classification reflecting the spectrum of two types of air targets, and it can improve the training speed of the algorithm. Based on this idea, we propose a KNN-SVM algorithm, which is based on the known spectrum of helicopter and fixed-wing spectrum template. The use of KNN training can filter the spectrum of helicopters, and the k nearest neighbor spectrums of each to-be-trained sample will to be sought. According to certain decision rules, the spectrum samples of the helicopters will be removed because of they are similar to the spectrum samples fixed-wing helicopter, then train again by using SVM algorithm. During the classification, in order to improve the recognition rate, we proposed ways to deal with through the accumulation.

In this section, at first, we analyzed the principles and methods to delete helicopter spectrum samples by using KNN, and then analyzed and gave an accumulation strategy. Finally, the major steps of KNN-SVM algorithm are given.

KNN is the promotion of 1-NN, the classification chosen nearest neighbors, to decide which type the majority of the neighbors belongs to. Suppose there are N samples. N_1 samples belongs to the ω_1 kind and N_2 samples belongs to the ω_2 kind,…， N_c samples belongs to the ω_c kind, The distinguish function is be defined as:

$$g_i(x) = k_i, i = 1, 2 \cdots, c \tag{4}$$

The rule follows: if $g_j(x) = \max k_i$, $x \in \omega_j$.

So, the use of KNN training can treat data set to filter the helicopters spectrum samples, and delete the fixed-wing spectrum samples according to (4).

Spectrum through deleted helicopter spectrum samples which are similar to the fixed-wing's ,it ensures the possibility of the optimal classification surface. However, in this case, most of the helicopters spectrum samples will be decided to fixed-wing.

In some specific applications, the radar system does not need to give the result of target recognition every time for each sub-system, but to give a little stability in the result of recognition, and accumulated strategies can achieve. For example, with the use of $1/n$ accumulation strategy, each observation is given an identifying intermediate result during processing, and each recognition decision as in a helicopter in n intermediate results, and the recognition result is the helicopter, or is fixed-wing. The stability of the recognition results can be ensured through this accumulation strategy.

The problem is the determination of the number of accumulation. In fact, without considering the frequency of repetition of the premise, to get at least a single flash pulse detection opportunities requires more than $50ms$, which is the beam on the target dwell time. For example, a single beam dwell time is $10ms$, then the target observation needs at least 5 times, and we can get larger than the beam on the target dwell time $50ms$, the number can be taken by $n = 50/10 = 5$. Of course, this observation can not guarantee that there must be rotor modulated information on the existence, because the observations may not be continuous, such as some mechanical scanning radar observations on the same target has almost single frame delay. However, the statistical average from a long view, this divide is quite a reasonable way.

KNN-SVM algorithm is given directly below the main steps:

(1) According to the size of the amount of training prior estimate of value k.

(2) Selecting Euclidean distance to measure the distance between the samples, that is, the distance between to-be-trained helicopter spectrum samples and the template spectrum samples is defined as：

$$D(x,y) = \left[\sum_{i=1}^{d} \left| x(j) - y(j) \right|^2 \right]^{\frac{1}{2}} \tag{5}$$

(3) Make sure the samples of the training helicopter spectrum as x, from the template sample set to find out the k nearest neighbors.

(4) According to equation (5) for decision, delete the sample which is decided as fixed-wing spectrum.

(5) Repeat the above four steps until all x are dealt with, to get the remaining to-be-trained samples of helicopter spectrum.

(6) With SVM, training the remaining to-be-trained samples of helicopter spectrum and the to-be-trained fixed-wing spectrum.

(7) According to radar observations of a single beam dwell time to determine the number n of accumulation.

(8) Using the trained SVM on the test set for testing, with the use of accumulation strategy $1/n$. If one is decided as helicopter in each n intermediate result, the recognition result is helicopter; otherwise, the recognition result is fixed-wing.

4. Simulation and Analysis

Make experiment based on the above algorithm, experimental software environment: Matlab 7.1/WIN XP; Hardware Environment: PⅣ 2. 66 G/512 MB.

The experiment data is from measured Doppler data set, which is measured by millimeter-wave radar. The sample types include both helicopters and fixed wing aircraft. The sample dimension is 64 (not including the classification of property). There are 1094 total samples, in which 547 samples in each class. There are 400 training samples, 200 samples in each class. There are 694 test samples, 347 samples in each class. There are 20 KNN templates, and 10 templates per class. In SVM training, C is taken to 1000. With the use of radial basis function and the parameter is taken to 0.5. The KNN parameter k is taken to 10. According to radar observations of a single beam dwell time to determine the number of accumulation $n = 6$.

Table 1 shows the experimental results of direct SVM and KNN-SVM method. Compared with the recognition results with directly SVM method, KNN-SVM method improves on the fixed wing of the recognition rate of the sample spectrum (97.41%) without using the case of the accumulation strategies, but the sample recognition rate of helicopter are not always effective (23.05%). Through the accumulation strategies, not reducing the recognition rate of fixed-wing spectrum sample of the premise (87.71%), it greatly improves the recognition rate of the helicopter spectrum sample (89.47%). At the same time, as the helicopter KNN spectrum of training samples removed, reducing the number of samples used for training to improve the training speed.

5. Conclusions

This paper presents a KNN-SVM-based air target recognition algorithms. At first, filter the to-be-trained samples set of helicopter spectrum with KNN algorithm, and delete the helicopter spectrum samples of a similar spectrum with fixed-wing. It can ensure the possibility of optimal classification which reflects the characteristics of these two types of air target spectrum. Then, in order to improve the recognition rate of helicopter spectrum which is similar to fixed-wing spectrum, the use of methods to deal with through the accumulation is proposed. And the corresponding accumulation corresponding are taken. Measured data results show that the method is effective.

6. Refereces

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Table I: Direct SVM method and KNN-SVM method in the measured results on the data set

Method	Samples of the actual number of training helicopter	Training time(second)	Accumulation strategies ($1/n$)	Recognition rate of helicopter	Recognition rate of fixed-wing aircraft	The average recognition rate
Direct SVM	200	17.6	1/6	100.00%	15.78%	57.89%
			none	79.82%	73.19%	76.51%
KNN-SVM	36	4.3	1/6	89.47%	87.71%	88.59%
			none	23.05%	97.41%	60.23%