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Research Article

A Novel Approach For Known and Unknown Target Discrimination Using HRRP

Daiying Zhou
Department of Electronic Engineering, University of Electronic Science and Technology of China, Chengdu, 611731, China

Abstract: In this study, a novel discrimination method for known and unknown target using High-Resolution Range Profile (HRRP), namely log-likelihood ratio score method, is proposed. The aim of this method is to minimize the error probability of discrimination by constructing the unknown target model when the data of unknown target is lack. The Gaussian Mixture Model (GMM) is introduced to model the statistical characteristics of target' HRRPs. The unknown-target model, which describes statistical distribution of unknown-target' HRRPs, is proposed. The statistics of unknown target can be computed approximately via finite known-target models in training database. The experimental results for measured data show that the discrimination rate of proposed method is about 88%, which is higher than that of discrimination method without unknown-target model.

Keywords: Known-target model, likelihood ratio score, target discrimination using HRRP, unknown-target model

INTRODUCTION

The high resolution range profile, which is the distribution of scattering centers on target along the radar line of sight, carries the information of a target, such as size, shape and relative position of strong scatter points, etc. This information is very useful in target classification. Generally, it is easier to get range profile of a target than obtaining a SAR image or an ISAR image, because it is no necessary to perform complicate moving compensation during one-dimensional imaging. The HRRP can directly serve as a feature vector for target identification. Additionally, HRRP-based recognition system can provide real-time identification performance; therefore, recently researchers have been interested in radar target recognition using HRRP.

Shi and Zhang (2001) presented a new neural network classifier, Kim *et al*. (2002) studied invariant features for HRRP (Suvorova and Schroeder, 2002; Zwart *et al*., 2003; Nelson *et al*., 2003) proposed a new iterated wavelet feature of HRRP, Wong (2004) applied the features in frequency domain for HRRP recognition, Du *et al*. (2006) studied the two distribution compounded statistical model for recognition HRRP. However, the above methods belong to classical pattern recognition, which only classify the targets that have been trained. In the real world, we may not obtain the first-hand data of rival country; therefore the aircraft may turn out to be an unknown target. In this case, the target recognition procedure must consist of discriminating and conventional pattern recognition. Figure 1 is a simplified block diagram.

In discriminating, a discriminator is used to determine whether the test target is a known-target or an unknown-target. If the test target is a known-target, then the test target's data is used to follow the conventional pattern recognition, otherwise the test target is rejected as an unknown-target. The discrimination is of great importance to improve the accuracy of recognition. Moreover, based on HRRPs of an unknown-target, the new database can be settled up and trained, making the new aircraft into a known-target, which leads to more complete database.

There has been little work in discrimination for known-target or unknown-target. Du *et al*. (2006) applied Gamma distribution and Gaussian mixture distribution to model statistical distribution of range cells for target HRRP and recognizes three aircraft targets using this two-distribution compounded model, but the discrimination for the known-target or unknown-target has not been discussed. Mitchell *et al*. (1999) studied the unknown-target rejection in target recognition process using the measure of confidence that is determined by the joint likelihood of the peak locations and amplitudes of the known-target. Shaw *et al*. (2000) considered the unknown-target rejection mechanism in HRR-ATR algorithm, which is implemented by first computing the maximum correlation score and next comparing the maximum score with the pre-determined threshold to reject the unknown-target. In general, the above methods reduce the error recognition rate of unknown-target to be erroneously identified as some known-target class, in unknown-target scenario. However these methods may gain low rejection rate of unknown-target when obtaining high discrimination rate of known-target due

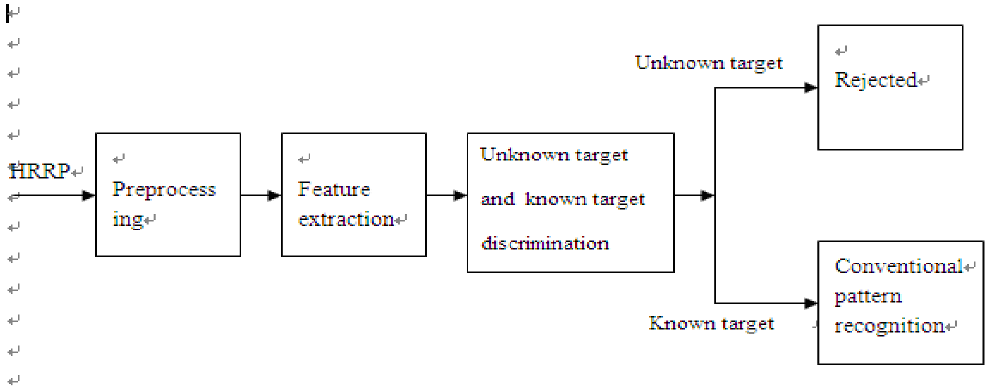

Fig. 1: Simplified function block diagram for target recognition with unknown-targets

to not establishing unknown-target model for making discriminating decision.

According to signal detection theorem, the problem of discrimination between known-target and unknown-target belongs to two-hypothesis detection.
Thus, we propose a new discrimination method, namely log-likelihood ratio score method. The aim of this method is to minimize the error probability of discrimination by constructing the unknown target model when the data of unknown target is lack. We use Gaussian Mixture Model (GMM) to model statistical distribution of the known-target' HRRP vectors. More importantly, we build up approximately unknown-target model from finite known-target models in training database, which solves problem about modeling distribution of unknown-target' HRRP vectors in an absence of unknown-target' HRRP data. Adopting unknown-target model in discrimination will result in good discrimination rate of both known-target and unknown-target. Experiments based on measured data are simulated to demonstrate the effectiveness of our discrimination approach.

METHODOLOGY

Log-likelihood ratio score base discrimination for single known-target: Assume target Ψ is a known-target with training data and then other targets are the unknown-targets with respect to target Ψ.

Given a range profile x and a hypothesized known-target Ψ, the goal of discrimination is to determine if x belongs to the known-target Ψ or not.

The single known-target discrimination can be restated as the following two-hypothesis test:

H_O : x is from the hypothesized known-target Ψ
H_1 : x is not from the hypothesized known-target Ψ or from the unknown-target

Let λ and λ′ denote the known-target model for hypothesis H_O and the unknown-target model for the alternative hypothesis H_1, respectively. The known-target model λ is built up by using all the training data O for hypothesized known-target and unknown-target model λ′ is created using the training data O′ of all unknown-targets with respect to the hypothesized known-target. The parameters of model λ and λ′ are solved by maximizing the likelihood functions P(O/λ) and P(O′/λ′).

According to the Bayes decision rule for minimum risk, the optimal decision rule for minimizing the probability of error for a given range profile X is:

$$\frac{p(x/H_0)}{p(x/H_1)} = \frac{p(x/\lambda)}{p(x/\lambda')}\begin{cases}\geq\theta & x\in H_0\\ <\theta & x\in H_1\end{cases} \tag{1}$$

where, $P(X/H_0)$, P(X/λ) and $P(X/H_1)$, P(X/λ′) are the Probability Density Function (PDF) for hypothesis H_O and H_1, respectively. θ is a predefined threshold. By taking logarithmic form, Eq. (1) becomes:

$$\log p(\mathbf{x}/\lambda) - \log p(\mathbf{x}/\lambda')\begin{cases}\geq\log\theta & x\in H_0\\ <\log\theta & x\in H_1\end{cases} \tag{2}$$

We define the log-likelihood ratio score:

$$S(\mathbf{x}) = \log p(\mathbf{x}/\lambda) - \log p(\mathbf{x}/\lambda') \tag{3}$$

Then, from Eq. (2) and (3), we get:

$$S(\mathbf{x})\begin{cases}\geq\log\theta & x\in H_0\\ <\log\theta & x\in H_1\end{cases} \tag{4}$$

Discrimination for multiple known-targets based on log-likelihood ratio score: In general, there are more than two known-targets in training database. Let C (>1) denote number of known-targets, then with respect to each known-target, the rest (C - 1) targets are referred as unknown-target. For instance, the unknown-targets of i^{th} known-target include 1^{th},…, $(i - 1)^{th}$, $(i + 1)^{th}$,… C^{th} known-target. The steps of discrimination algorithm are listed below:

- For each target in training database, the known-target model is built up using training data.
- Given a range profile X, according to Eq. (3), compute the log-likelihood ratio score for each known-target Si(x) (i = 1, 2,…, C), where the unknown-target model is determined by corresponding unknown-targets' training data.
- The threshold $Iog\theta_i (i = 1, 2, \ldots, C)$ is determined via statistical analysis on the log-likelihood ratio scores' distribution during the training process.
- Discrimination decision rule is given by:

if $S_i(x) \geq Iog\theta_i$ for any of a i, then $x \in$ known-target
or if $S_i(x) < Iog\theta_i$ for all i, then $x \in$ unknown-target (5)

Known-target model: An important step in the above discrimination is the selection of the actual likelihood function. The choice of this function is mainly dependent on the distribution of target HRRPs. We use Gaussian Mixture Models (GMM) to represent the likelihood function of known-target. There are two main reasons for using GMM as a representation of known-target HRRP's distribution. The first reason is that individual component densities of GMM may model some underlying set of scatter centers for HRRP. It is well known that a HRRP may contain many composite scatter centers and the distribution of a composite scatter center's amplitude can be represented by Gaussian component density. Thus, it is reasonable to use GMM to model the probability density function of target HRRP. The second reason is the empirical observation that a linear combination of Gaussian basis function is capable of representing a large class of sample distributions. One of the powerful ability of the GMM is that it can form smooth approximation to arbitrarily-shaped densities.

For a D-dimensional sample vector, x a Gaussian mixture density, which is used for likelihood function, is a weighted sum of M uni-modal Gaussian densities:

$$p(\mathbf{x}/\lambda) = \sum_{k=1}^{M} w_k p_k(\mathbf{x}) \tag{6}$$

where, W_k, K = 1, 2,.., M are mixture weights, satisfying the constraint $\sum_{k=1}^{M} W_k = 1$ and $P_k(X)$, K = 1, 2,…, M, are the Gaussian densities. Each component density is parameterized by a $D \times 1$ mean vector, u_k and a $D \times D$ covariance matrix, Σ_k:

$$p_k(\mathbf{x}) = \frac{1}{(2\pi)^{D/2} |\mathbf{\Sigma}_k|^{1/2}} \exp\{-\frac{1}{2}(\mathbf{x}-\mathbf{u}_k)^T \mathbf{\Sigma}_k^{-1}(\mathbf{x}-\mathbf{u}_k)\} \tag{7}$$

The complete Gaussian mixture density is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities. Collectively, these parameters are denoted below:

$$\lambda = \{w_k, \mathbf{u}_k, \mathbf{\Sigma}_k\} \;\; k = 1, 2, \cdots, M \tag{8}$$

The GMM can have several different forms depending on the choices of covariance matrices. For example, there may be one covariance matrix per Gaussian density, one covariance matrix for all Gaussian densities in a known-target model, or a single covariance matrix shared by all known-target models. These covariance matrices can also be full (each entry may be non-zero) or diagonal (only diagonal entries are nonzero). However, we use only one diagonal covariance matrix for a known-target in this study, which also leads to good discrimination performance.

Given a collection of training sample vectors, the GMM model parameters are estimated using the iteratively Expectation-Maximization (EM) algorithm, which can iteratively update model parameters to monotonically increase the likelihood of estimated model for observed vectors. The iterative equations of EM for training a GMM can be found in Reynolds (1992).

Unknown-target model: In case of symmetrical cost and equal prior probabilities for the known-target and unknown-target model, $log\theta$ is equal to 0 and this is a theoretic threshold. Of course, if the statistics of all unknown-targets corresponding to each known-target can be obtained to build up the unknown-target model, the decision rule of (4) is optimal. However, it is difficult to get enough unknown-targets' data to create this model due that the data of the unknown-targets is unknown. In general, the log-likelihood value of the unknown-target model is set to zero in solving Eq. (3), i.e., it means the unknown-target' statistics is not used in discriminating. This may lead to high error discrimination rate for the unknown-targets. Thus, it is of great importance to establish the unknown-target model that represents the statistics of the unknown-targets to improve the discrimination rate. In this study, we propose a method to approximately estimate an unknown-target model from finite known-target models in training database.

In a C known-targets pool, for each known-target, we use rest (C - 1) known-target models to construct corresponding unknown-target model. The operating steps are stated below:

- Find the model of every known-target λ_i by maximizing the likelihood score $P(O_i/\lambda_i)$, where O_i is training dataset for i^{th} known target
- The unknown-target model for i^{th} known-target λ'_i is given by:

$$\lambda'_i = \{\lambda_{s(1)}, \cdots, \lambda_{s(j)}, \cdots, \lambda_{s(C-1)}\} \quad (9)$$

$s(j) \in [1, C]$ and $s(j) \neq i$

- This likelihood score $P(x/\acute{\lambda}_i)$ is computed by following two methods
- **Mean method:** In mean method, the log-likelihood score for an unknown-target model is the mean of N_m highest log-likelihood scores in model set of (9):

$$\log p(x/\lambda'_i) = \frac{1}{N_m} \sum_{j=1}^{N_m} \log p(x/\lambda_{s(j)}) \quad (10)$$

where, the log-likelihood scores $logP(x/\lambda_{s(j)})$ in (9) is arranged in descending order and $N_m \in [0, C-1]$. As $N_m = 0$, implicitly $logP(x/\acute{\lambda}_i) = 0$.

- **Maximum method:** In the maximum method, the log-likelihood score for the unknown-target model is the maximum one among scores of model set of (9):

$$\log p(\mathbf{x}/\lambda'_i) = \max_{j \in [1, C-1]} \log p(\mathbf{x}/\lambda_{s(j)}) \quad (11)$$

EXPERIMENTAL RESULTS

Data description: To demonstrate the effectiveness of above discrimination method, several experiments are performed on measured data of five types of airplanes, i.e., A320, A319, B737, B752 and E145. The parameters of the targets and radar are shown in Table 1 and 2, respectively. Training dataset for generating the known-target model library and test dataset for evaluating the discrimination performance are from two different collections of measurements. The measured HRRP is a 200-dimensional vector.

Preprocessing: There are several factors affecting performance for HRRP based discrimination, such as target-aspect sensitivity, time-shift sensitivity and amplitude-scale sensitivity. Thus, HRRP will be preprocessed using following steps, to decrease the influence of these factors on discrimination:

Table 1: Parameters of radar

Radar parameters	Center frequency	Bandwidth
	3 GHz	150 MHz

Table 2: Parameters of airplanes

Planes	Length (m)	Width (m)	Height (m)
A319	33.80	34.10	11.76
A320	37.57	34.09	11.76
B737	33.40	28.90	11.13
B752	47.30	38.00	13.50
E145	27.96	20.53	7.100

- Normalize each HRRP, i.e., $\|X\| = 1$
- Apply Fast Fourier Transform (FFT) to each HRRP, to achieve shift alignment on HRRP. Because the amplitude of FFT is time invariant with shift
- The range of target-aspect is divided into several sectors. The size of each sector is 5°. The variation of HRRPs in a sector largely decreases due to small aspect range, which leads to reducing target-aspect sensitivity

GMM:

Initialization: To investigate the relation between model initialization and discrimination performance, known-target models are built up using different initialization methods for a discrimination experiment.

This experiment includes 5 class targets (A319, A320, B737, B752 and E145), first four class targets (A319, A320, B737 and B752) of which are taken as known-target and the rest one (E145) is taken as unknown-target. The known-targets are modeled using GMM with one diagonal covariance matrix shared by all mixture component densities per known-target. They are trained using the first collection of measured data. Testing is done using the 2^{nd} collection of measured data.

The first initialization method applies C-Mean clustering algorithm to congregate the training data into 4 subclasses automatically, which corresponds to the initial mixture component densities. The means and the average diagonal covariance matrix of all subclasses are served as the initial model for EM training. The second initialization method randomly choose 4 vectors from a target' training data for the initial means of model and use an identity matrix for the initial covariance matrix. The initial value of weight W_k is $\frac{1}{4}$. In unknown-target model, set $N_m = 2$. The decision threshold $log\theta_i (i = 1, 2, \ldots, C)$ is set to 0. The results of discrimination are shown in Table 3.

Table 3: The discrimination rate based on GMM for two initialization methods (%)

Target class	C-Mean clustering initialization method (number of iteration is 5)	Randomly choosing initialization method (number of iteration is 5)
A319 (known target)	76	75
A320 (known target)	87	89
B737 (known target)	92	90
B752 (known target)	91	86
E145 (unknown target)	95	97
Average discrimination rate	88	87

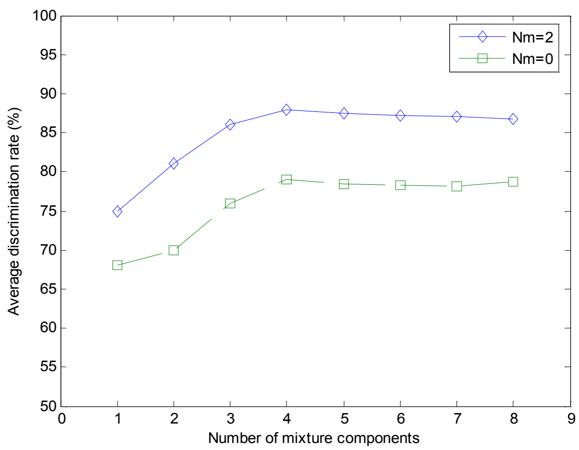

Fig. 2: Discrimination performance as a function of the number of component densities per known-target model

From Table 3, it is seen that there is no significant difference in discrimination performance between the initialization methods listed above. It is also observed that both methods required the same number of EM iterations for the convergence of likelihood function. These results show that optimal initialization schemes are no necessary for training Gaussian mixture model for a known-target.

Model order: Regarding the discrimination performance based on the number of component densities per model, the following experiment is done based on 2 collections of measured airplane data. The GMM with 1 to 8 component Gaussian densities per known-target is trained. There is a diagonal covariance matrix per component. In an unknown-target model, $N_m = 2$ and $N_m = 0$. The decision threshold $Iog\theta_i(i = 1,2,\ldots,C)$ is set to 0. Figure 2 shows the average correct discrimination rates versus the number of Gaussian components.

In Fig. 2, it is observed that the average discrimination rate is a sharp increase, when the number of mixture components is from 1 to 4. And average discrimination rate is insensitive to the number of mixture components, when the number of mixture components is above 4. These results demonstrate that appropriate model order is 4 based on these measured dataset, which means that there is minimum model order to maintain good discrimination performance for these dataset.

Table 4: The discrimination ratio using two known-target models (%)

Target class	GMM	GM
A319 (known target)	76	68
A320 (known target)	87	73
B737 (known target)	92	77
B752 (known target)	91	78
E145 (unknown target)	95	83
Average discrimination rate	88	76

The known-target model: In this experiment, we compare performance of two known-target models-GMM and Gaussian Model (GM). The training dataset and testing dataset are the same as those in previous experiments. Each known-target is modeled by a 4 components GMM with one diagonal covariance matrix shared by all mixture components of model. The GM of known-target is built up by computing mean and covariance matrix using training dataset of corresponding target. Set $N_m = 2$ for the unknown-target model. The decision threshold $Iog\theta_i(i = 1,2,\ldots,C)$ is set to 0. The results are shown in Table 4.

It is observed from these results, the average discrimination ratio of GM is 12% lower than that of GMM. The reason is that GM only uses one Gaussian component to describe the distribution of target HRRPs, but real distribution of HRRPs is too complicate to represent only using a Gaussian component. Thus, the GMM is suitable to approximate the distribution of target HRRPs. And hence, only GMM is used to model known-target in later experiments.

Two computation method for likelihood of unknown-target model: In this experiment, we compare the performance of the mean method and maximum method for likelihood score computation of unknown-target model. The training data and testing data used in this experiment are the same as those in the previous experiment. The number of the highest log-likelihood scores to be averaged, denoted as N_m, varies

Table 5: The discrimination rate for two computation method of likelihood for unknown-target (%)

Target class	Mean method ($N_m = 0$)	Mean method ($N_m = 1$) (Max. method)	Mean method ($N_m = 2$)	Mean method ($N_m = 3$)
A319 (known target)	71	73	76	74
A320 (known target)	76	83	87	86
B737 (known target)	80	86	92	88
B752 (known target)	81	84	91	89
E145 (unknown target)	85	88	95	92
Average discrimination rate	79	83	88	86

from 0 to number of models in Eq. (9). For $N_m = 0$, it means that log-likelihood of the unknown-target model is zero. The maximum method is given by $N_m = 1$.

The results are shown in Table 5. Some conclusions can be drawn from this table:

- At $N_m = 0$, the correct discrimination ratio is the lowest. This is because that no unknown-target model is used in computing likelihood ratio scores.
- At $N_m = 1$, i.e., maximum method, the discrimination performance is not optimal. The reason is that only one known-target model with highest likelihood scores is used in computing the likelihood ratio scores.
- For this case, the best result is obtained by setting $N_m = 2$.

Performance comparison for different discrimination methods: We also use Confidence Measure based Unknown-Target Rejection (CMUTR) method (Mitchell and Westerkamp, 1999) and Maximum Correlation Score Threshold based Discrimination (MCSTD) method (Shaw *et al*., 2000) to demonstrate effectiveness of the Log-Likelihood Ratio Score based Discrimination (LLRSD) method proposed in this study. In log-likelihood ratio score based method, GMM is used to model known-targets and the likelihood of unknown-target model is computed using Mean method ($N_m = 2$). The decision threshold $log\theta_i (i = 1,2, \ldots, C)$ is set to 0. The experimental data is the same as described above. The experiments, in which the Gaussian white noise is added to HRRPs of targets, are simulated for different SNR. The average discrimination rates of three methods versus SNR are shown in Fig. 3.

It is obvious that with SNR between 5 and 10 dB, the performance of these methods is sensitive to noise. With SNR (above 15 dB), the average discrimination rates of LLRSD is higher than those of CMUTR and MCSTD. The reason is that LLRSD method which utilizes unknown-target model to approximately represent distribution of unknown-target' HRRPs, but CMUTR method and MCSTD method only applies the known-target model.

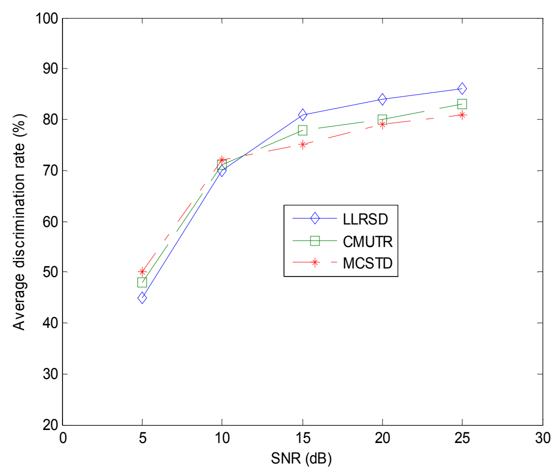

Fig. 3: The average discrimination rates of LLRSD, CMUTR and MCSTD versus SNR

CONCLUSION

This study has proposed the log-likelihood ratio score method for known-target and unknown-target discrimination using HRRP. It is derived from the theorem of Bayes test for minimum risk. The GMM and unknown-target model are applied to represent the target HRRP's distribution and unknown-target HRRP's distribution, respectively. The experiments on measured dataset show that:

- There appears to be an appropriate model order for GMM to model known-targets, due to low computation amount and good discrimination performance
- For known-target, GMM outperforms the GM
- The mean method to compute the likelihood score of unknown-target model is superior to the maximum method if appropriately choosing the averaged number of the highest log-likelihood scores
- With SNR (above 15 dB), the average discrimination rate of the method proposed in this study is higher than that of CMUTR (Mitchell and Westerkamp, 1999) and MCSTD (Shaw *et al*., 2000), which demonstrates the effectiveness of the proposed method

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