RADAR HIGH RANGE RESOLUTION PROFILES RECOGNITION BASED ON WAVELET PACKET AND SUBBAND FUSION[1]

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ABSTRACT

Radar automatic target recognition (ATR) by using high range resolution profiles (HRRPs) is addressed. A subband fusion structure is proposed based on wavelet packet transforming. Multiple adaptive Gaussian classifiers (AGCs) are built for each subband, and the output of each subband classifiers are combined together to make a final decision. Comparing with the traditional wideband recognition approach, i.e., single band approach, the proposed approach can achieve better recognition performance, and is more robust to noise as well. Example results based on the measured data are given to show the efficiency of the proposed method.

1. INTRODUCTION

Radar automatic target recognition (ATR) is to identify the unknown target from its radar echoed signatures. Targets high-range-resolution (HRR) radar signatures, including high range resolution profiles (HRRPs), synthetic aperture radar (SAR) and inverse synthetic aperture radar (ISAR) images, contain more detail target structure information than that of the low-range-resolution radar signatures, therefore, they play a very important role in radar ATR community. Comparing with radar target SAR and ISAR images, target HRRP is more easier to be acquired, which makes the HRRP to be a promising signatures for Radar ATR [1-4,8]. In the paper, we will address radar ATR based on target HRRPs.

A number of radar HRRP recognition algorithms are proposed after decades of development in the field. Most of the researchers put their focus on extracting promising features and designing powerful classifiers. Actually, another efficient approach is to design multiple classifiers for different features, and combine the output of multiple classifiers together to achieve classification performance improvement [5,6]. In the paper, we proposed a radar HRRP recognition approach based on multiple subbands classifiers combination structure.

The remainder of the paper is organized as follows. In Sec 2, two widely used HRRP recognition algorithms, maximum correlation coefficient (MCC) classifier and adaptive Gaussian classifier (AGC), are introduced briefly, and the link between the two algorithms is analyzed. In Sec 3, a subband fusion structure based on wavelet packet is proposed. Example results based on measured data are given in Sec 4. Followed by the conclusion of the paper.

2. MCC AND AGC CLASSIFIERS

When performing radar HRRP recognition, three issues need to be considered. First, the HRRP amplitude is a function of target distance, radar transmitted power, receiver sensitivity time control (STC) waveform, adaptive gain control factor, etc. Therefore, the HRRP amplitude should be normalized before performing recognition. A generally used approach is 2-norm normalization. Second, there is uncertainty of HRR profile's time-shift existing in real system, this uncertainty should be compensated, which is referred as range alignment in literatures. Finally, radar HRRPs vary as a function of target-radar orientation, thus the classifier should have the ability to handle this target aspect sensitivity. A straightforward method is to build multiple representation models for different target aspect sectors. In what follows, we will introduce two widely used HRRP recognition algorithms briefly, namely, maximum correlation coefficient (MCC) classifier and adaptive Gaussian classifier (AGC).

2.1 Maximum correlation coefficient classifer [1]

Given a template HRRP data set contains M HRRPs denoted as $\{X_{Ti}(n), i=1,2,...,M, n=1,2,...,N\}$ and a test HRRP denoted as $X(n)$, assume they are 2-norm normalized, the MCC between test HRRP and ith template is defined as

$$r_i = \max_{\tau} \sum_{n=1}^{N} X_{Ti}(n) X(n-\tau) \tag{1}$$

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A larger r_i means more similar between the test HRRP and the template. The label of the test HRRP is determined as the label of the template which holds the MCC with the test profile.

It is shown that the average HRRP corresponding to a target aspect sector is a promising signature to represent the target scatterers distribution structure in the sector [3]. Therefore, the average HRRPs associated with different target aspect sectors are generally used as templates in the above MCC classifier.

2.2 Adaptive Gaussian classifier (AGC) [2,8]

For a training data set of target *i*, AGC using Gaussian distribution to model the data as

$$p(X|T_i) = \frac{1}{(2\pi)^{N/2}|\Sigma_i|^{1/2}} \exp\left\{-\frac{1}{2}(X-\mu_i)^T \Sigma_i^{-1}(X-\mu_i)\right\} \qquad (2)$$

where μ_i and Σ_i are the mean range profile and covariance matrix of *i*th target, respectively, which can be estimated from the training data. The posteriori probability $p(T_i|X)$ can be written as

$$p(T_i|X) = \frac{p(X|T_i)p(T_i)}{p(X)} \qquad (3)$$

Assume the priors $p(T_i, i = 1,2,...,I)$ for different targets are equal, omit the constant term, the discriminant function of AGC normally take the form

$$y_i(X) = -\frac{1}{2}(X-\mu_i)^T \Sigma_i^{-1}(X-\mu_i) - \frac{1}{2}\ln|\Sigma_i| \qquad (4)$$

The label of the test HRRP is determined as the label of the Gaussian model which holds the maximum $y(X)$.

Generally, in order to represent the statistical property of HRRPs associated with different target aspect sectors, multiple Gaussian models are built for one target. In addition, the test HRRP need to be range aligned before calculate the discriminant factor using (4). One method is to search the range shift compensation factor by maximizing the discriminant factor usng (4) directly. An alternative method is to align the test HRRP with the mean profile. The latter can be implemented via Fast Fourier Transform, it is more computational efficient than the former, but our experiment results show the classification performance of the former is better than that of the latter slightly. To save the compute time, we use the latter range alignment method in the paper. Generally, the underlying probability density of HRRP data are not Gaussian distribution, power transformation is usually used as a preprocessing technique to transform HRRP data more Gaussian like [2].

If we assume the covariance matrix is diagonal, and the covariance of each range cells and each targets are all same, then the above discriminant function degenerates to Euclidean distance based method, which is actually equivalent to the MCC classifier.

The MCC classifier only uses the first order statistics, mean vector, to perform classification, while AGC uses both the mean vector and the covariance matrix to perform classification. Therefore, AGC generally outperforms MCC classifier. But AGC requires a large enough training data samplers to estimate the mean vector and variance matrices, if there is only small number of training data available, a larger estimation variance may be introduced in mean vector and covariance matrix, in this case, the performance of AGC will be decreased.

3. SUBBAND FUSION STRUCTURE

Instead of designing single classifier to perform a pattern recognition task, combining multiple classifiers for different features provides an alternative way to do it. This approach has received extensive attention in pattern recognition community recently, and has been successful applied in various problems [5-7].

By following the concept of multiple classifiers combination, a subband fusion classifier structure for radar HRRP classification is proposed, as shown in Fig.1. A similar structure used for speech recognition can be found in [7]. Under this structure, the original HRRP is decomposed into multiple subbands by wavelet packet based on Daubechies wavelet. For each subband, a classifier is built. The output of multiple classifiers are combined together to make a final decision.

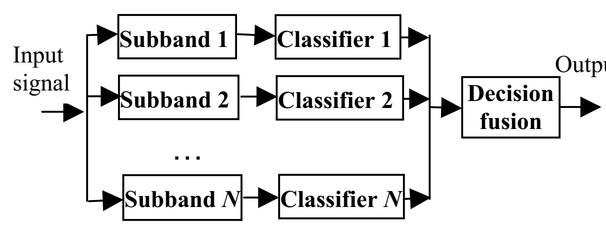

Fig.1 Subband fusion classifier structure

3.1 Data modeling

After M layers wavelet packet decomposition, 2^{M-1} subbands signal will be obtained. For each subband signal, it is downsampled by 2^{M-1} comparing with the original HRRP signal. Using Gaussian distribution to model the subband signal, the discriminant function of AGC at subband level can be written as

$$y_{i,k}(X_k) = -\frac{1}{2}(X_k-\mu_{i,k})^T \Sigma_{i,k}^{-1}(X_k-\mu_{i,k}) - \frac{1}{2}\ln|\Sigma_{i,k}| \qquad (5)$$
$$i = 1,2,...,I, \qquad k = 1,2,...,K$$

where $\mu_{i,k}$ and $\Sigma_{i,k}$ are the mean range profile and covariance matrix of *i*th target and *k*th subband, respectively.

3.2 Classifiers combination rules

The method of combining multiple classifiers is an interesting issue and received extensive attention. If only labels are available from the output of classifiers, a majority vote or label ranking are generally used. If the output of the classifiers are interpreted as belief value or evidence, belief functions and Dempster-Shafer techniques are generally used. If the classifiers can provide posterior probability, a common theroritical framework is developed in [6], which includes various classifiers combination rules as special cases, such as the sum rule, product rule, majority voting, etc. Due to space limit, we only consider three kinds of combination rules in the paper, namely, product rule, sum rule and belief integration.

3.2.1 Product rule

Assume all the subband signals are statistical independent each other, then the conditional joint probability distribution of subband signals can be written as

$$p(X_1, X_2, ..., X_K | T_i) = \prod_{k=1}^{K} p(X_k | T_i) \tag{6}$$

Using the Bayes formula, after derivation, the label of the test HRRP can be determined by

$$i = \arg\max_j \sum_{k=1}^{K} y_{j,k}(X_k) \tag{7}$$

3.2.2 Sum rule

The sum rule is derived under an assumption that the a posteriori probabilities computed by the respective classifiers will not deviate dramatically from the prior probability [6]. Obviously, this assumption is much stronger than the statistical independent assumption used in the product rule. Based on the sum rule, the label of the test HRRP can be determined by

$$i = \arg\max_j \sum_{k=1}^{K} P(T_j | X_k) \tag{8}$$

3.2.3 Belief integration

Belief integration method is based on the confusion matrices of individual classifiers. Assume I classes with K classifiers, and the output of each classifier is the label of test HRRP. Suppose the output of kth classifier is

$$e_k(X_k) = j, \quad j \in \{1, 2, ..., K\} \tag{9}$$

and its confusion matrix is

$$CM_k = \begin{pmatrix} n_{11}^k & n_{12}^k & \dots & n_{1K}^k \\ n_{21}^k & n_{22}^k & \dots & n_{2K}^k \\ \dots & \dots & \dots & \dots \\ n_{K1}^k & n_{K2}^k & \dots & n_{KK}^k \end{pmatrix} \tag{10}$$

The element n_{ij}^k means that n_{ij}^k samples of class i are assigned to class j by the kth classifier.

The belief value of a decision made by the kth classifier is calculated as follows [9]

$$\begin{aligned} & b_k(X \in class\ i | e_k(X) = j) \\ & = p_k(X \in class\ i | e_k(X) = j) = \frac{n_{ij}^k}{\sum_{l=1}^{K} n_{lj}^k \xi_{il}^k} \end{aligned} \tag{11}$$

where $\xi_{ij}^k = n_{i.}^k / n_{j.}^k$ and $n_{i.}^k = \sum_j^K n_{ij}^k$. And the label of the test HRRP can be determined as

$$i = \arg\max_j \sum_{k=1}^{K} b_k(X \in class\ j | e_k(X)) \tag{12}$$

3.3 Additional consideration

When applying the above subband fusion structure for radar HRRP recognition, several issues need to be paid attention to.

First, the wavelet packet decomposition is not translation invariant, the subband signals of a HRRP are not the same as that of its shifted version. If the number of the shifted range cell is integer times of subband number, the range shift number of each subband signal is integer, in this case, the range shift can be compensated at the stage of range alignment. Otherwise, extra effort needs to be taken to handle this issue. Rather than following the idea of translation invariant wavelet transform, we build the range shift effect into the statistical model. For each training HRRP sample, we perform wavelet packet decomposition for its K range shifted versions, each one is in turn shifted by one range cell. The Gaussian distribution models used for AGC are trained by all the training samples and their range shifted samples. At test stage, the wavelet packet decomposition is performed for the test HRRP only once.

Second, when performing range alignment for the subband signal, the range shift compensation factors should be same for all the subband signals. We use the MCC criterion to do range alignment at the lowest frequency band, the signals at other subbands are shifted by the same scale. Also one can use a more complex method to perform range alignment by combining all the subband signals together, but our experiment results show its performance improvement is very slightly.

4. EXAMPLER RESULTS

The data used to evaluate the classification performance are measured from a C band radar with bandwidth of 400MHz. The HRRP data of three airplanes, including An-26, Yark-42 and Cessna Citation S/II, are measured continuously when the target are flying. The measured data of each target are divided to several segments, the training data and test data are chosen from different data segment respectively, which means the target orientation corresponding to the test data and training data are different, the maximum elevation difference between the test data and training data is about 5 degrees. For each target, about 6000 HRRPs are used for training Gaussian models, and totally about 40000 HRRPs are used for test. For each target, 50 Gaussian models are trained associated with different target aspect sectors. The confusion matrices used for belief integration are calculated by using the training data at training stage.

An interesting question is how to choose system parameters, such as subband number, wavelet form and power transformation factor, etc. These parameters are chose empirically in the paper. We only consider Daubechies wavelet with different order here, experiment results show that 4 order Daubechies wavelet achieves best performance. The subband number is chose as 4, and the power transformation factor is chose as 0.15.

The average classification rates for different classifier parameters are shown in Table 1. Since AGC utilizes more statistical information of the training data, its classification performance is better than that of the MCC classifier. The performance of multiple subbands fusion structure based on product rule and belief integration are better than that of using single band, namely, the original HRRP, except for the sum rule, which is even worse than the single band case. This result is different with that shown in [6], in which the sum rule generally outperforms the product rule for handwritten digit recognition. It is probably because the assumption used by the sum rule is stronger than that of the product rule for HRRP classification application, as discussed in Section 3. Among different system configurations, the multiple subband structure with belief integration combination rule achieves the best performance, it is because the belief integration rule treats different subband classifiers according their classification capabilities, while the sum rule and product rule treat each subband classifiers equally. Shown in Fig. 2 are the average classification rates of AGC under different SNR levels. It is shown that using original HRRP, single band case, for classification is very sensitive to noise, it totally breaks down when SNR less than 20dB, while using 4 subbands is more robust to noise. This is not surprise because the SNR level at each subband is different due to the asymmetrical energy distribution of HRRPs, therefore, under low SNR case, there still one or several subband classifiers work well.

5. CONCLUSIONS

Radar HRRP recognition based on wavelet packet and subband fusion structure is proposed in the paper. Experiment results show this approach can improve the classification performance and is more robust to noise as well. Because the underlying distribution model is simplified by subband processing, it is more accurate to model it using Gaussian model. This should be the main factor responsible for the performance improvement.

6. REFERENCES

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Table 1. Average classification rates for different system configurations

	Single band	Four subbands		
		Sum rule	Product rule	Belief integration
AGC	0.8990	0.8819	0.9098	0.9296
MCC	0.8820	N/A	N/A	0.9110

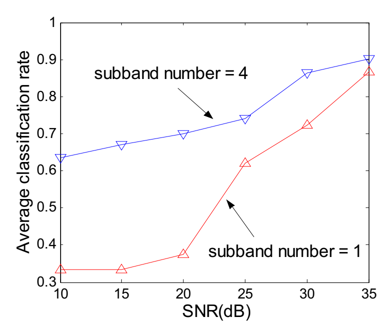

Fig. 2. Average classification rate vs. signal noise ratio