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EFFICIENT RADAR TARGET RECOGNITION USING A COMBINATION OF RANGE PROFILE AND TIME-FREQUENCY ANALYSIS

S. K. Han and H. T. Kim

Department of Electronic & Electrical Engineering
Pohang University of Science and Technology
San 31, Hyoja-Dong, Nam-Ku, Pohang, Kyoung-buk 790-784, Korea

S. H. Park

Department of Electronics Engineering
Pukyong National University
Busan 608-737, Korea

K. T. Kim

School of Electrical and Computer Science
Yeungnam University
214-1, Dae-Dong, Gyeongsan-si, Kyoung-buk 712-749, Korea

Abstract—In this paper, a new hybrid classification method using both range profile (RP) and time-frequency image is proposed. The time-frequency image is obtained using the short-time Fourier transform before calculating the RP and this image is used for classification. 2-Dimensional Principal Components Analysis (2DPCA) is used to further compress the time-frequency image and to derive useful features from the image. The proposed method achieves a higher correct classification ratio than existing methods, especially when the signal-to-noise ratio is low.

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Corresponding author: S. H. Park (radar@pknu.ac.kr).

1. INTRODUCTION

Radar target recognition is an important military challenge. Among the information from a typical radar signal, the range profile (RP) can be used to classify objects [1–7]. The RP shows the radar cross section (RCS) distribution of a target along the radial distance, which can provide information on the position and scattering strength of the targets scattering centers at that aspect (Fig. 1) [8–10]. A 1-dimensional classifier using the RP is suitable for real-time target recognition because it is relatively fast and is not influenced by the targets motion [11]. Compared to other classifiers based on scattering centers [12] or inverse synthetic aperture radar images [13–16], RP has the advantage of the computing time, memory space, and simplicity. However, because the RP is obtained by taking the absolute value of the range-compressed radar signal, the phase information which contains useful information is excluded [11]. In addition, when the signal-to-noise ratio (SNR) is low, classification accuracy is degraded considerably [11] due to the contamination of the RP by the noise.

The phase of the range-compressed radar signal contains useful information about the target. Thus, the time-frequency image (TFI) constructed using the phase information of the range-compressed signal can provide effective features of each target and can improve the correct classification ratio P_c if used in combination with the RP [17]. Therefore, we propose a target recognition method that uses a combination of the RP and TFI. The RP is normalized to achieve level invariance and shifted using correlation to achieve translational invariance. Then, training data yielding high correlation values with a test RP are selected in descending order of correlation. The simple short-time Fourier transform (STFT) is used to construct TFIs of the selected RPs, which are then used identify the unknown target. 2DPCA [18] is used to compress the TFI and extract the features and a simple nearest-neighbor classifier classifies the compressed image. In experiments using data obtained by measuring six scale models in a compact range, the combination of the TFI and the RP improves classification accuracy considerably when the SNR is low.

2. METHODS

2.1. Time Frequency (TF) Method

The TF method is used to represent the power distribution of frequency over time [19]. In this paper Short-Time Fourier Transform (STFT) which is easily implemented by the simple fast Fourier transform (FT) is used as the TF method. Input signal $s(t)$ at time τ is transformed

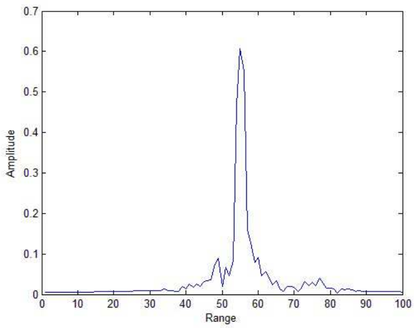

Figure 1. Sample RP.

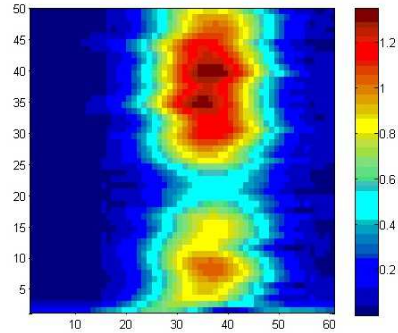

Figure 2. Sample TFI using STFT.

by STFT [19]:

$$\mathrm{STFT}(t,\omega)=\int_{-\infty}^{\infty} s(\tau)\gamma^{*}(\tau-t)e^{-j\omega\tau}d\tau, \tag{1}$$

where γ denotes the window function (in this paper, a Hamming window), t is the time, ω is the frequency. The discrete version of (1) is (2):

$$\mathrm{STFT}[m,n]=\sum_{k=0}^{L-1} s[k]\gamma[k-m]e^{-\frac{2\pi nk}{L}}, \tag{2}$$

where $s[k]$ is the range-compressed complex signal, m is the sampled time, n is the sampled frequency, k is the time index, L is the window length. The RP can be calculated by taking the absolute value of $s[k]$ (Fig. 1). A Sample TFI is denoted in Fig. 2.

2.2. 2DPCA and Feature Extraction

TFI is inappropriate for classification because it contains a significant amount of redundant information. Therefore, 2DPCA is applied to reduce the redundancy and to extract useful features. Compared to conventional PCA, 2DPCA requires less memory, is faster, and provides more accurate classification [18].

Let $\mathbf{A}$ denote the m-by-n image data and $\mathbf{X}$ denote a projection axis, then projected feature vector $\mathbf{Y}$ is

$$\mathbf{Y}=\mathbf{AX} \tag{3}$$

Given M training images, the jth training image is denoted by an m-by-n matrix $\mathbf{A}_j$ ($j=1,2,\ldots,M$), the average image of all training samples is $\bar{\mathbf{A}}$, and the image covariance (scatter) matrix is defined by

$$\mathbf{G_t} = \frac{1}{M}\sum_{j=1}^{M}\left(\mathbf{A}_j - \bar{\mathbf{A}}\right)^T\left(\mathbf{A}_j - \bar{\mathbf{A}}\right) \tag{4}$$

Then, $\mathbf{X}$ is a projection axis that maximizes the generalized total scatter criterion [18] defined by

$$J(\mathbf{X}) = \mathbf{X}^T\mathbf{G_t}\mathbf{X} \tag{5}$$

The optimal projection axis $\mathbf{X_{opt}}$ is the eigenvector of $\mathbf{G_t}$ corresponding to the largest eigenvalue. A set of projection axes $\mathbf{X_1}, \ldots, \mathbf{X_d}$, can be chose, which are orthonormal constraints that maximize the criterion $J(\mathbf{X})$. $\mathbf{X_1}, \ldots, \mathbf{X_d}$, are orthonormal eigenvectors of $\mathbf{G_t}$ corresponding to the d largest eigenvalues. and

$$\mathbf{X_D} = [\mathbf{X_1} \ldots \mathbf{X_d}] \tag{6}$$

$\mathbf{X_D}$ can be used to extract the feature matrix $\mathbf{B}$ of the image:

$$\mathbf{B} = \mathbf{A}\mathbf{X_D} = [\mathbf{Y_1} \ldots \mathbf{Y_d}] \tag{7}$$

The result of PCA is a vector but the result of 2DPCA is an m-by-d matrix. d is specified by the user.

2.3. Classifier

A simple nearest neighbor classifier is used to classify $\mathbf{B}$ obtained using 2DPCA. The distance between two arbitrary feature matrixes $\mathbf{B_i} = [\mathbf{Y_1^{(i)}}, \mathbf{Y_2^{(i)}}, \ldots, \mathbf{Y_d^{(i)}}]$ and $\mathbf{B_j} = [\mathbf{Y_1^{(j)}}, \mathbf{Y_2^{(j)}}, \ldots, \mathbf{Y_d^{(j)}}]$ is defined by

$$d(\mathbf{B_i}, \mathbf{B_j}) = \sum_{k=1}^{d}\left\|\mathbf{Y_k^{(i)}} - \mathbf{Y_k^{(j)}}\right\|, \tag{8}$$

where $\|\mathbf{Y_k^{(i)}} - \mathbf{Y_k^{(j)}}\|$ denotes the Euclidean distance between the two principal component vectors $\mathbf{Y_k^{(i)}}$ and $\mathbf{Y_k^{(j)}}$. Then, the class of an unknown target image $\mathbf{B_u}$ compressed using 2DPCA is determined by

$$\hat{i} = \min_i d(\mathbf{B_u}, \mathbf{B_i}), \tag{9}$$

where $\mathbf{B_i}$ is a training image that belongs to the ith target.

3. CLASSIFICATION PROCEDURE

The proposed method (Fig. 3) consists of a training phase and a test phase. In the training phase, RCS data of the training target are collected in the compact range. RPs are constructed from the measured data using the absolute value of the range compressed data obtained by a simple inverse FT (IFT). TFIs are constructed using (1) and (2) and compressed using 2DPCA. In the test phase, RCS data of the real target in flight are collected and RPs are calculated by the same procedure. Then, RPs in the training database are coarsely sifted using the maximum correlation for all shifts of the test RP. Note that, whenever calculating the correlation between the test RP and the training RP, the test RP must be shifted one by one to find the maximum correlation. Because this step consumes much time, it is conducted in frequency domain using the convolution theorem as follows:

$$maxcor = \max\{|IFT[FT[RP_1]FT[RP_2]^*]|\} \tag{10}$$

In this step, TFIs corresponding to RPs which yield highest $r\%$ (sifting ratio) of *maxcors* among the total training RPs are selected and the rest are discarded. If $r = 0\%$, only RPs are used as a feature vector,

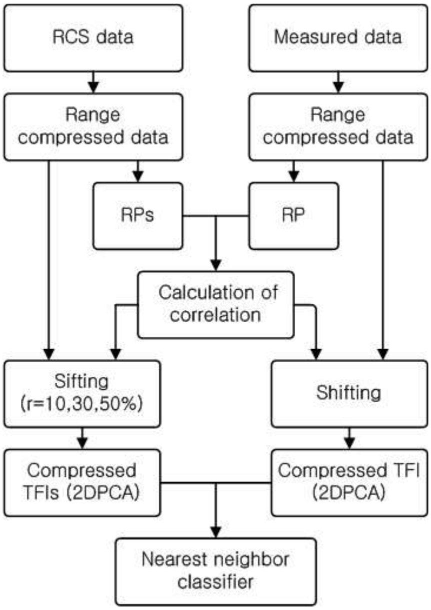

Figure 3. Procedure used in proposed method.

and if $r = 100\%$, only TFIs are used as a feature vector. In this step, the locations of *maxcor* for all selected TFIs are stored to construct test TFIs that are invariant to translation. In the classification, the range compressed test data are shifted by the stored shift of each training TFI and the test TFI is constructed for each of the chosen TFIs, the final decision is made based on (9).

4. EXPERIMENTAL RESULTS

An experiment was conducted to measure the RCS data in a compact range using scale models of six aircraft F4, F14, F16, F114, F22, and Mig29. The size of scale models is 1 m. The frequency varied from 8.3 to 12.3 GHz, and the bandwidth was 4 GHz. (3.75 cm resolution) in 0.01 GHz increments, yielding 401 point stepped frequency samples. Aspect angles range from 0 to $+30^\circ$ in 0.5° increments. Therefore, 61 samples were obtained for each target and the total size of the data set was $61 \times 6 = 366$. In classification, the 366 samples were divided into a training set and a test set. The training set was constructed by uniformly sampling the aspect angle per every 1°. Therefore, $30 \times 6 = 180$ samples were used to construct the training database and the remaining 186 samples were used for classification. To simulate the effect of noise, additive white Gaussian noise was added to the measured RCS data to achieve the desired SNR. The classification was performed 100 times for each SNR and the average P_c was used as the classification result.

Table 1. Confusion matrix 1: SNR = 0 dB, 2DPCA dimension = 2, $r = 10\%$ $P_c = 91.94\%$.

	F4	F14	F16	F117	F22	Mig29
F4	30	1	0	0	0	0
F14	0	28	0	0	1	2
F16	0	1	28	0	0	2
F117	0	0	0	31	0	0
F22	0	0	0	0	31	0
Mig29	3	4	1	0	0	23

In constructing TFIs using the range compressed data, the 40-point Hamming window was used with the number of overlap equal to 39 points for each neighboring time sample. Then, each 40-point set of windowed data was zero-padded to 50 points and fast Fourier transform (FFT) was conducted to construct the TFI for each time shift.

Table 2. Confusion matrix 2: SNR = 5 dB, 2DPCA dimension = 2, $r = 10\%$ $P_c = 98.39\%$.

	F4	F14	F16	F117	F22	Mig29
F4	30	1	0	0	0	0
F14	0	31	0	0	0	0
F16	1	0	30	0	0	0
F117	0	0	0	31	0	0
F22	0	0	0	0	31	0
Mig29	0	1	0	0	0	30

Classifications were performed for various SNRs and for each SNR, the effect of sifting ratio r was tested using $r = 0\%$ (RP only), 10%, 30%, 50%, and 100% (TFI only). In addition, the effect of the 2DPCA dimension d on the classification was tested using $d = 2$, 3, and 5. Sample confusion matrix denoted in Table 1, Table 2. P_c increased in proportion to SNR (Figs. 4–6). At SNR > 10 dB, P_cs for all r values differed by 2%. However, at SNR = 0 dB, the P_cs obtained by proposed method with $r = 10\%$, 30%, and 50% were much higher than those with $r = 0\%$ (RP only) and 100% (TFI only). This demonstrates the efficiency of the proposed method. P_cs decreased as d increased: this decrease is due to the data redundancy.

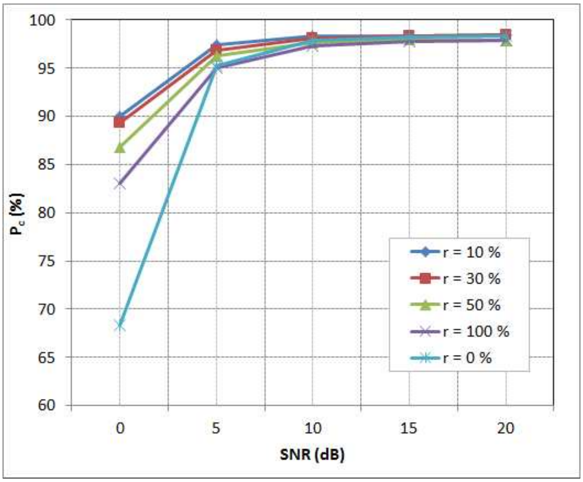

Figure 4. P_c versus SNR. 2DPCA-dimension = 2.

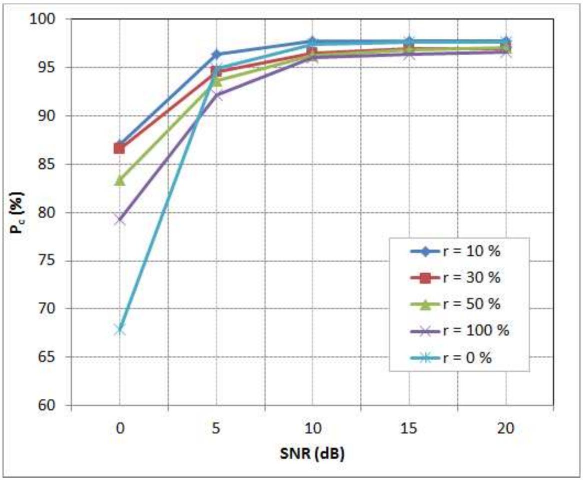

Figure 5. P_c versus SNR. 2DPCA-dimension = 3.

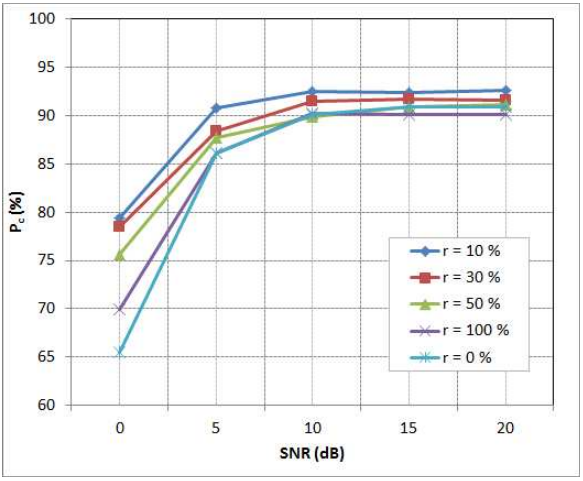

Figure 6. P_c versus SNR. 2DPCA-dimension = 5.

5. CONCLUSION

In this paper, a new target classification scheme based on the RP and TFI was proposed. This scheme has both level-invariance and translational-invariance. This hybrid method correctly classifies targets more often than methods that use only RP or TFI, especially when SNR is low. The optimum value of r is dependent on the classification scenarios. Thus, further investigation must be conducted to determine the optimum r. In addition, 2DPCA was demonstrated to be very suitable for extracting the features of the TFI. However, P_cs were degraded due to the redundancy when the dimension of the compressed feature increased. The proposed method using a combination of two methods can be extended to include other efficient radar signatures such as inverse synthetic aperture radar, natural frequency, and jet engine modulation.

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