Performance Comparison of Target Classification in SAR Images Based on PCA and 2D-PCA Features

Changzhen QIU, Hao REN, Huanxin ZOU, Shilin ZHOU

School of Electronic Science and Engineering, National University of Defense Technology, Changsha 410073, China

Abstract

Feature extraction is an important step for target classification in SAR images. Principal component analysis (PCA) is common in pattern recognition, and has been used widely for target classification in SAR images. In order to utilize PCA, two-dimensional image has to be arranged to an observation vector. However, two-dimensional PCA (2D-PCA), which is developed from PCA, can extract features from two-dimensional SAR image directly. Although 2D-PCA is consistent with PCA in theory essentially, which represents original data by extracting principal components with high variance values by linear transformation, they perform distinctly due to the difference of data processing methods. Based on the theoretical analysis and classification experiment using MSTAR data, this paper compares PCA and 2D-PCA systematically and roundly.

Keywords: Synthetic Aperture Radar image, Feature Extraction, Principal Component Analysis, Two-dimensional PCA

1. Introduction

Feature extraction is an important step for target classification in SAR images. Feature extraction transforms original target image through some transformation, and gets new data that interprets the target more simply and effectively. Depending on whether the transformation is linear or nonlinear, target features can be classified into linear feature and nonlinear feature. The extraction of linear feature employs information of target, so linear feature refers to certain physical meanings, such as length and width, edge, peak and so on. The extraction of nonlinear feature is another case, it is a pure technology for data process and transforms image without employing any information of target, so nonlinear feature doesn't refer to any physical meaning.

PCA is a common technology for linear feature extraction, and has been used widely in pattern recognition. Research on the use of PCA in SAR ATR is also a hot topic recently [1-7]. From the open literatures we can conclude that, classification method based on PCA features is better than traditional Bayesian classification method based on conditional Gauss model (CGBC) [1]; PCA also outperforms other linear features, such as independent component analysis (ICA), Hu moments, wavelet transform (WT) and so on [2]. In order to use PCA, two-dimensional image has to be arranged into an observation vector. But two-dimensional PCA (2D-PCA), which is developed from PCA, can extract features from SAR image directly. 2D-PCA is proposed for face recognition [9], and it also performs well in SAR ATR [4, 5].

Based on the theoretical analysis of PCA and 2D-PCA, this paper compares these two methods systematically by classification experiments using MSTAR data. In this paper, Section 2 gives a brief theory introduction of PCA and 2D-PCA. Section 3 describes three SAR image pre-processing methods that can improve the quality of SAR image. Section 4 is the design of classifiers. Section 5 is some analysis and discussion of the experiments results.

2. Feature Extraction

2.1. PCA

PCA is based on the assumption that high information corresponds to high variance [2]. After the extraction of PCA features, original data is projected to a new coordinate space, and each coordinate axis in the new coordinate space represents a principal component vector. The first principal component vector is the direction that accounts for as much of the variance as possible (the direction along which the variance is a maximum); the second principal component vector is defined by the direction orthogonal to the first for which the variance is a maximum, and so on [8]. If X is original data, Y is projection data, and composites all the principal component vectors to H, so

$$Y = XH \tag{1}$$

The column vectors of Y are independent, and are ordered by variances. If the first few principal components account for most of the variation, then these may be used to describe the data, thus leading to a reduced-dimension representation.

PCA can only process one-dimensional data, so image pixels should be arranged into an observation vector first. If the training samples after being arranged are $\{X_1, X_2, \ldots X_p\}$, then using PCA to extract features should follow the following four steps [1, 7]:

(1) Compute the mean of training samples

$$\bar{X} = \frac{1}{p}\sum_{i=1}^{p} X_i \tag{2}$$

(2) Compute the covariance matrix of training samples

$$Q = \sum_{i=1}^{p} (X_i - \bar{X})^T (X_i - \bar{X}) \tag{3}$$

(3) Compute all the eigenvalues and eigenvectors of Q. Then choose the eigenvectors correspond to the k most largest positive eigenvalues to form the transformation matrix V ($V \in R^{N \times k}$);

(4) All consecutive rearranged training image-pixel vectors are stacked together to form the observation matrix X. So the training samples' feature matrix C can be got by

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$$C = XV \tag{4}$$

Testing image-pixel vector T 's features vector y can be got by

$$y = TV \tag{5}$$

2.2 2D-PCA

PCA can only process one-dimensional data while 2D-PCA has been extended to two-dimensional data matrix. 2D-PCA is consistent with PCA in theory essentially, and both of them are based on the assumption that high information corresponds to high variance. The difference is that 2D-PCA extracts features from two-dimensional image directly, thus leading to covariance matrix of lower dimension and smaller computation burden.

There are four steps to be followed to use 2D-PCA to extract features from SAR image [4, 5].

(1) If $\{X_1, X_2, \ldots X_p\}$ are the training images, then centre them

$$I_i = X_i - \bar{X} \tag{6}$$

where

$$\bar{X} = \frac{1}{p}\sum_{i=1}^{p} X_i \tag{7}$$

(2) Compute the covariance matrix of the training images

$$Q = \sum_{i=1}^{p} I_i^T I_i \tag{8}$$

(3) Choose the eigenvectors correspond to the $k1$ most largest positive eigenvalues to form the transformation matrix V_{row} .

(4) For each training image X_i , its feature matrix is

$$C_i = (X_i - \bar{X})V_{row} \tag{9}$$

For a testing image T , its feature matrix is

$$C = (T - \bar{X})V_{row} \tag{10}$$

2D-PCA reduces the dimension of the covariance matrix availably. But a new problem is that 2D-PCA can only eliminate the correlations between rows, and leaves the correlations between columns without dealing. It induces that the feature dimension of 2D-PCA is larger than that of PCA, which requires more resources for storage and classification. To resolve this problem, literature [5] proposes a two-stage 2D-PCA feature extraction technology.

Based on the work of 2D-PCA, two-stage 2D-PCA regards the features matrix C_i as new training samples and repeats the course of 2D-PCA. If choose the eigenvectors correspond to the $k2$ most largest positive eigenvalues to form the transform matrix V_{col} , then the feature matrix of a training image can be got by

$$B_i = Z_i V_{col} = V_{row}^T (X_i - \bar{X})^T V_{col} \tag{11}$$

And the feature matrix of a testing image can be got by

$$B = V_{row}^T (T - \bar{X})^T V_{col} \tag{12}$$

Two-stage 2D-PCA resolves the feature dimension problem of 2D-PCA to some extend. Because two-stage 2D-PCA eliminates the correlations of rows and columns separately, so its feature dimension is still larger than that of PCA.

3. SAR Images Pre-processing

Before extracting features, SAR image should be pre-processed in order to improve the quality. Considering the characteristics of PCA, SAR image is segmented, enhanced, normalized, and transformed using 2D-FFT in this paper [5].

3.1 Segmentation

SAR image includes target region and background region. The pixels of background region have a variance value due to their fluctuation, which would decrease the performance of target classification. So it is necessary to depress the variance of background region. Segmentation can reduce the influence of the variance of background region effectively.

In this paper, SAR image is segmented to binary image by CFAR first [10], then overlaying the binary image on the original image gets target image. In addition, in order to eliminate redundant data and improve computational efficiency, target image should be shear into a smaller size. The three kinds of target (BTR70, BMP2 and T72) that used in this paper from MSTAR is about 40×40 in image, but the original image is about 128×128 , so we shear the target image to 44×44 , which is large enough to cover the whole target region.

3.2 Enhancement and Normalization

PCA and 2D-PCA features can be enhanced by power-law transformation. If $H(x, y)$ is the segmented target image, and $K(x, y)$ is the image after power-law transforming, then

$$K(x, y) = [H(x, y)]^{\alpha} \tag{13}$$

where α is a constant. In SAR image, the pixels that implicate the most information of target are the peak value points. The peak value points will have higher variance after being transformed by power-law transformation, which turns out to be useful for classification. The value of α is hard to decide, but not the higher the better. It is proved to be good for MSTAR images when we choose $\alpha = 5$.

In practice, to solve the impact of distance between target and radar, we normalize the target image

$$J(x, y) = K(x, y) / \sqrt{\sum_x \sum_y |K(x, y)|^2} \tag{14}$$

where J, K denotes the former and latter normalized image respectively.

3.3 2D-FFT

To extract feature, target should be centred in SAR image. But it is hard to centre target accurately. Fourier transformation is a common technology for data process. Image data can be transformed to frequent domain by 2D-FFT. In frequent domain, the problem can be resolved perfectly. In this paper, image is transformed by 2D-FFT, and half of the amplitude of Fourier is used as inputs for PCA or 2D-PCA feature extraction.

4. Classifiers

Nearest-neighbor is the most resultful classifier for PCA and 2D-PCA features [1, 2, 5]. Nearest-neighbor computes the distances between testing sample and all training samples, and then chooses the target type corresponding to the minimum distance as the type of the testing sample. The distance of PCA, 2D-PCA and two-stage 2D-PCA are defined as following.

PCA: the distance between testing sample features y^T and training sample features $C^T = (y_1, y_2, \dots y_p)$ is defined as

$$d_i = \| y^T - y_i \|_2 \tag{15}$$

2D-PCA: the distance between testing sample features $C = (y_1, y_2, \dots y_k)$ and training sample features $C_i = (y_1^i, y_2^i, \dots y_k^i)$ is defined as

$$d(C, C_i) = \sum_{j=1}^{k_1} \| y_j - y_j^i \|_2 \tag{16}$$

Two-stage 2D-PCA: the row distance between testing sample features $B = (y_1, y_2, \dots y_{k_1})^T$ and training sample features $B_i = (y_1^i, y_2^i, \dots y_{k_2}^i)$ is defined as

$$d_r(B, B_i) = \sum_{j=1}^{k1} \| y_j - y_j^i \|_2 \tag{17}$$

The column distance between testing sample features $B = (y_1, y_2, \dots y_{k_2})$ and training sample features $B_i = (y_1^i, y_2^i, \dots y_{k_2}^i)$ is defined as

$$d_c(B, B_i) = \sum_{j=1}^{k_2} \| y_j - y_j^i \|_2 \tag{18}$$

So the total distance between a testing sample and a training sample is defined as

$$d(B, B_i) = d_r(B, B_i) + d_c(B, B_i) \tag{19}$$

5. Analysis and Discussion of Experimental Results

In this paper, MSTAR SAR radar image database [13] including three types of target (BTR70, BMP2, and T72) is used for experiment. BTR70 contains only one variant; BMP2 contains three variants of 9563, 9566 and c21; T72 contains three variants of 132, 812 and S7. All the images distribute uniformly on $0 \sim 360^0$ pose angle of the target. We use BTR70 (c71), BMP2 (9563) and T72 (132) at 17^0 depress angle as training datasets, and all images at 15^0 depress angle as testing datasets. So training datasets can be separately from testing datasets, and we can also test out the performance of classification algorithm when pose angle or variant of testing image is different from training images. The details of the training and testing datasets can be got from table 1.

Table 1. Training and testing datasets

Training datasets (17^0)	Number of samples	Testing datasets (15^0)	Number of samples
BTR70(c71)	233	BTR70(c71)	196
BMP2(9563)	233	BMP2(9563)	195
		BMP2(9566)	196
		BMP2(c21)	196
T72(132)	232	T72(132)	196
		T72(812)	195
		T72(s7)	191

Classification based on PCA, 2D-PCA, two-stage 2D-PCA is experimented respectively, following the flow chart as Fig.1 shows.

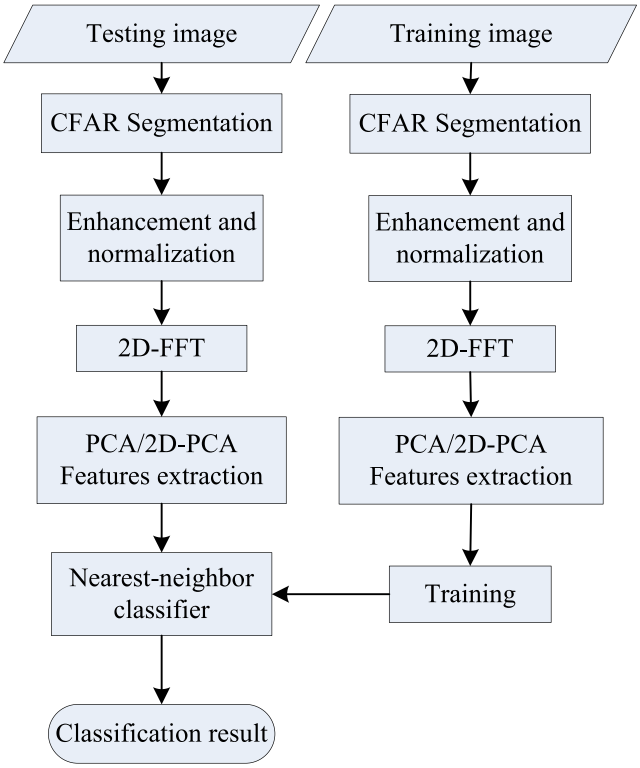

Fig.1. Flow chart of classification based on PCA and 2DPCA features

The variation of accuracy with feature dimension of PCA and 2D-PCA is given in Fig.2. The accuracy of two-stage 2D-PCA is changing with both row feature dimension and column feature dimension and the relation is three-dimensional, so it is shown in Fig.3 by itself. Table 2 is the feature dimension required of the three methods on different accuracy. Table 3 is comparison of feature dimension and classification time of the three methods when each of them achieves their highest accuracy.

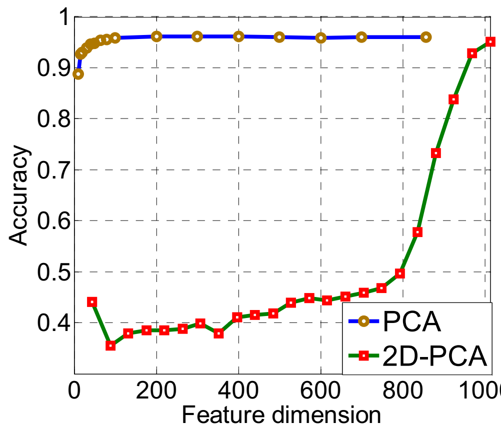

Fig.2. Variation curve of accuracy with feature dimension of PCA and 2D-PCA

Fig.2. shows that the accuracy of PCA increases faster than that of 2D-PCA. 2D-PCA eliminates only the correlation between rows, and leaves the correlations between columns without dealing. It induces that the feature dimension of 2D-

PCA is larger than that of PCA. Fig.3. shows that two-stage 2D-PCA gets high accuracy only when both row and column feature dimension is large enough. Table 2 shows that two-stage 2D-PCA improving a lot than 2D-PCA in reducing redundancy. But the feature dimension of two-stage 2D-PCA is still larger than PCA, which accords with the analysis in section 2.2.

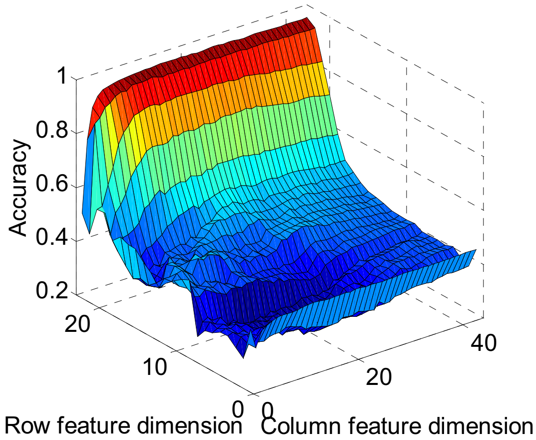

Fig.3. Variation curve of accuracy with row and column feature dimension of two-stage 2D-PCA

Table 2. Feature dimension required of the three methods on different accuracy

Accuracy	PCA	2D-PCA	Two-stage 2D-PCA
91%	12	978	92
92%	14	978	105
93%	21	978	105
94%	34	978	161
95%	60	1022	230

Table 3 is the comparison of feature dimension and classification time of the three methods when each of them achieves their highest accuracy. Because the training of classifier can be finished outline, so the classification time means the time spends on feature extraction of testing image and classification. The experiment is carried out in a Pentium 4 CPU 1.8 GHz and RAM 512M computer. Table 3 shows that PCA overwhelms other two methods in highest accuracy, feature dimension, and classification time.

Table 3. Comparison of the three methods when each of them achieves their highest accuracy

Feature extraction	Accuracy	Feature dimension	Classification time
PCA	96.19%	200	9.3s
2DPCA	95.09%	1022	39.4s
Two-stage 2D-PCA	95.90%	621	40.5s

The purpose of using 2D-PCA and two-stage 2D-PCA to reduce the dimension of covariance matrix is to improve the efficiency of classification. But the new problem of feature dimension expanding makes the classification time of 2D-PCA and two-stage 2D-PCA is even more than PCA, and the accuracy hasn't been improved meanwhile. So it can be concluded that PCA is more usable than 2D-PCA and two-stage 2D-PCA for target classification in SAR images.

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References

[1] Amit Kumar Mishra and Bernard Mulgrew, "Radar signal classification using PCA-based features", in proceeding of ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing, 2006, pp.1104-1107.

[2] Yinan Yang, Yuxia Qiu and Chao Lu, "Automatic target classification experiments on the MSTAR SAR images", in proceedings of the Sixth International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing and First ACIS International Workshop on Self-Assembling Wireless Networks (SNPD/SAWN'05), 2005, pp.2-7.

[3] Zhiguo HE, Jun LU and Gangyao KUANG, "A Fast SAR Target Recognition Approach Using PCA Features", in proceedings of the 4th International Conference on Image and Graphics, ICIG 2007, pp.580-585.

[4] Xiaoguang Lu, Ping Han and Renbiao Wu, "Two-Dimensional PCA for SAR Automatic Target Recognition", in Proceedings of 2007 1st Asian and Pacific Conference on Synthetic Aperture Radar, APSAR 2007, pp.513-516.

[5] Liping Hu, Jin Liu, Hongwei Liu, Bo Chen and Shunjun Wu, "Automatic Target Recognition based on SAR images and Two-Stage 2D-PCA features", Dianzi Yu Xinxi Xuebao/Journal of Electronics and Information Technology, 2007, 30(7), pp.1722-1726.

[6] Ying Wang, Ping Han and Renbiao Wu, "Analysis of PC Number Selection in SAR ATR", in Proceedings of 2007 1st Asian and Pacific Conference on Synthetic Aperture Radar, APSAR 2007, pp. 521-524.

[7] Amit K. Mishra, "Validation of PCA and LDA for SAR ATR", in proceedings of IEEE Region 10 Annual International Conference, 2007, pp.1-6.

[8] Andrew R.Webb, "Statistical Pattern Recognition", Second Edition, Wiley & Sons Ltd: Chicheste, 2002.

[9] Yang Jian, Zhang David, Frangi Alejandro F and Yang Jing-Yu, "Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, 2004, 26(1), pp.131-137.

[10] G. Kuang, G. Gao, Y. Jiang, et al. Synthetic Aperture Radar Target Detection Theory Algorithms and Applications. Changsha: National University of Defense Technology Publishing House, 2007.

[11] www.mbvlab.wpafb.af.mil/public/sdms/datasets/mstar.