ISAR Target Recognition Based on Two-dimensional Locality Preserving Projection

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Abstract. It is well known that the relationship between different radar target data is often nonlinear, so the recognition rate will decrease if the traditional linear subspace methods are used to reduce the dimension of inverse synthetic aperture radar (ISAR) images. Recently, Locality Preserving Projections (LPP), a kind of manifold learning algorithm, is proposed for ISAR target recognition. But the ISAR images must be vectorized in LPP algorithm, which would result in the problem of singularity, and the local structural information from original images is easy to lose. In this paper, a novel ISAR target recognition algorithm is presented by using two-dimensional Locality Preserving Projections (2DLPP). The proposed 2DLPP algorithm is based directly on 2D ISAR images rather than 1D vectors as conventional LPP does. The simulated experimental results suggested that 2DLPP has better classification performance comparing to PCA, LDA and LPP.

1. Introduction

In recent years, automatic target recognition (ATR) based on inverse synthetic aperture radar (ISAR) images has received considerable attention from the researchers\cite{1}--\cite{4}. Different from the optical images which can describe the overall shape of the targets, ISAR images just represent the sparse distribution of scattering centers. Also, the dimension of the ISAR images is high, and the ISAR images of the same target will be changed when the target is in different distance, attitude and rotation rate. Therefore, it is important to adopt proper and robust techniques for dimension reduction and feature extraction in ISAR target recognition.

At present, some linear subspace methods, such as Principal Component Analysis (PCA)\cite{5}--\cite{6}, Linear Discriminant Analysis (LDA)\cite{7}--\cite{8} and Independent Component Analysis (ICA)\cite{9}--\cite{10}, are widely applied in radar target recognition domain. However, these methods only can find the linear structure of the observation data, but actually the ISAR data will be non-linear due to the complex movement of the target. For this reason, better results will be received if non-linear techniques are applied.

Nowadays, a number of research efforts have shown that many high-dimension observation data possibly reside on a non-linear sub-manifold which is controlled by a small number of implicit parameters. The idea of manifold learning provides us a new way to dimension reduction via analyzing the intrinsic dimension of high-dimension sampling data. Techniques that have been proposed for this purpose include Isometric Mapping (ISOMAP)\cite{11}, Locally Linear Embedding (LLE)\cite{12} and Laplacian Eigenmap (LE)\cite{13}. However, they yield maps that only defined on the
training data points and it remains unclear how to evaluate the novel test data points. So these methods might not be used in ISAR image target recognition directly. In order to overcome the above shortcomings in manifold learning, He et al put forward a new algorithm called Locality Preserving Projections (LPP)[14] and applied it to face recognition successfully[15]. LPP is a linear subspace method derived from Laplacian Eigenmap, it not only has the advantages of linear subspace method, but also has the capability of manifold learning.

In 2010, Qiang He et al proposed LPP for ISAR target recognition[16], they pointed that the ISAR images do reside on a low-dimension sub-manifold embedded in the high-dimension ISAR image space, which is controlled by fewer parameters, such as attitude angle, cross-range scale and position, etc., and the better recognition performance is acquired with the low-dimension feature obtained by LPP, comparing to PCA and LDA.

However, there are two disadvantages in this application: (1) the 2D ISAR images must be transformed into 1D vector, this will result in the problem of singularity of matrices, when the number of samples is far smaller than the dimension of samples; (2) The image-to-vector transform will lose the local structural information embedded in the original ISAR images which may be more important for target recognition.

In order to avoid these problems, a novel ISAR target recognition algorithm is presented by using two-dimension Locality Preserving Projections (2DLPP) [17-19]. The proposed 2DLPP algorithm is based directly on 2D ISAR image matrices rather than 1D vectors as conventional LPP does. The simulated experimental results suggest that the 2DLPP algorithm has better classification performance comparing to LPP algorithm.

2. Locality Preserving Projections (LPP)
LPP is the optimal linear approximations to the Laplacian Betrami operator on the manifold [14]. Therefore, although it is a linear method, it seems to recover the important aspects of the intrinsic non-linear manifold structure by preserving local structure.

Given a set of high-dimension data points \( X = \{ x_1, x_2, \ldots, x_m \} \) in high-dimension Euclidean space \( R^n \), find a transformation matrix \( W \) that maps these \( m \) points to a set of points \( Y = \{ y_1, y_2, \ldots, y_m \} \) in \( R^l \) \((l < n)\), such that \( y_i = W^T x_i \) is the one-dimension representation of original data vector \( x_i \). The transformation matrix \( W \) will be obtained by minimizing the following objective function

\[
J = \sum_{i,j} [y_i - y_j]^T S_{ij}
\]  

(1)

In Equation (1), the local relationships among the input data vectors are described by similarity matrix \( S \), where the similarity relationship is defined as follows:

\[
S_{ij} = \begin{cases} 
\exp(-\|x_i - x_j\|^2 / t), & e(x_i, x_j) = 1 \\
0, & e(x_i, x_j) = 0 
\end{cases}
\]  

(2)

In Equation (2), \( e(x_i, x_j) \) is an indicator function designating whether \( x_i \) and \( x_j \) are neighbors and \( t \) is the heat kernel factor. The neighborhood of a given input vector \( x_i \) can be defined as the \( k \)-nearest vectors to \( x_i \).

Following some simple algebraic steps, the above objective function reduced to follows:

\[
\frac{1}{2} \sum_{i,j} [y_i - y_j]^T S_{ij} = \text{tr}(W^T XLX^T W)
\]  

(3)

Where \( L = D - S \) is Laplacian matrix. The matrix \( D \) is a diagonal matrix of \( m \times m \), its entries are \( D_{ii} = \sum S_{ij} \). Matrix \( D \) provides a natural measure on the data points, the bigger the value \( D_{ii} \) is, the more "important" \( y_i \) is. Impose a constraint to the objective function as follows:

\[
Y^T DY = 1 \Rightarrow W^T XDX^T W = 1
\]  

(4)

Finally, the transformation matrix \( W \) that minimizes the objective function is given by the maximum eigenvalue solution to the generalized eigenvalue problem:

\[
XLX^T W = \lambda XDX^T W
\]  

(5)
3. Two-Dimension Locality Preserving Projections (2DLPP)
Consider a set of ISAR sample images \( \{A_i\}_{i=1}^{k} \in \mathbb{R}^{m \times n} \), design a linear transformation \( y_i = AW \), which maps the original \((m \times n)\)-dimension image space into an \((m \times d)\)-dimension feature space. Here, \( W \in \mathbb{R}^{m \times d} \) is the projection matrix.

The objective function of 2DLPP method is also equation (1):

\[
J = \sum_{i,j} \|y_i - y_j\|^2 S_{ij} = \sum_{i,j} \|AW - AW\|^2 S_{ij}
\]

\[
= \sum_{i,j} \|A_i - A_j\|^2 S_{ij} = W^T (\sum_{i,j} (A_i^T A_i - A_j^T A_j) S_{ij}) W
\]

\[
= W^T \sum_{i,j} (A_i^T S_{ij} I_m A_i - A_j^T S_{ij} I_m A_j) W
\]

\[
= W^T A^T [(D - S) \otimes I_m] AW
\]

\[
= W^T A^T [L \otimes I_m] AW
\]  

(6)

Where \( A = [A_1, A_2, ..., A_k] \), the definition of \( S, L \) and \( D \) is the same as LPP, \( \otimes \) is defined as Kronecker product. Furthermore, in order to remove the arbitrary scaling factor in the embedding, a constraint is imposed as followings:

\[
\sum_{i,j} D_{ij} X_i^T X_j = 1 \Rightarrow W^T (\sum_{i} D_{ii} A_i^T A_i) W
\]

\[
= W^T A^T (D \otimes I_m) AW = 1
\]  

(7)

Then the minimization problem of the objective function becomes

\[
\min_W W^T A^T (L \otimes I_m) AW
\]  

(8)

The transformation vector \( W \) is given by the minimum eigenvector solution to the generalized eigenvalue problem:

\[
A^T (L \otimes I_m) AW = \lambda A^T (D \otimes I_m) AW
\]  

(9)

Through solving equation (9), the best projection vector \( W \) can be obtained.

4. Proposed classification algorithm
In this section, we describe the details of our method.

4.1 Data pre-processing
In this study, we perform two steps to complete the pre-processing task. The first step is to extract the target from the background clutter or noise. Here, we assume that the signal-to-noise ratio (SNR) or signal-to-clutter is relatively high, so we can select a threshold to remove the background noise and clutter from the original image. Thus, those pixels with higher values than the threshold are considered as target, and the remaining pixels are set to zero. Nowadays, there are many methods to help us to determine the threshold, such as edge detection, histogram-based segmentation techniques and intensity-based method, and so on. But their performance is not always reliable [20]. In this paper, we use the Constant False Alarm Rate (CFAR) algorithm to obtain an adaptive threshold.

The next step is to normalize the ISAR image intensity. As we all know that the radar echo intensity will be influenced by many factors, such as distance, receiver gain, and so on. For this reason, it is necessary for us to normalize the ISAR image intensity in order to remove the disadvantages arising from the varying intensity. In this paper, we use the whole energy to normalize the ISAR image. Suppose \( I(x,y) \) is the intensity of a random pixel on the ISAR image, then the normalized intensity of this pixel can be expressed as:
\[ I_n(x_i, y_j) = \frac{I_n(x_i, y_j)}{\sum_{i=1}^{M} \sum_{j=1}^{N} I_n(x_i, y_j)} \]  \hspace{1cm} (10)

As a result, the influence of the varying intensity in recognition is removed.

4.2 Dimension reduction based on 2DLPP

Now the entire procedure of dimension reduction based on 2DLPP algorithm is summarized as follows:

1) Create a graph \( G \) with \( n \) nodes: The \( i \)th node denotes the ISAR image \( A_i \), put an edge between the \( i \)th and \( j \)th node, if \( A_i \) is among the \( k \) nearest neighbors of \( A_j \), or \( A_j \) is among the \( k \) nearest neighbors of \( A_i \), and also \( A_i \) and \( A_j \) must have the same class label.

2) Compute the weights: If node \( i \) and node \( j \) are connected, put a similarity weight \( S_{ij} \) on it, otherwise zero. There are two variations for weighting the edges: to change the default, adjust the template as follows:
   
   (1) heat kernel: If there is an edge between node \( i \) and node \( j \), put \( S_{ij}=\exp (-|A_i-A_j|^2/t) \), where \( t \) is a suitable constant, otherwise \( S_{ij}=0 \). In our work, the heat kernel method is applied for its stability.
   
   (2) simple-minded: \( S_{ij}=1 \), if node \( i \) and node \( j \) are connected by an edge, otherwise \( S_{ij}=0 \). In our work, the heat kernel method is applied for its stability.

3) Eigenmap: Compute the eigenvectors and eigenvalues for the general eigenvalue problem:
   \[ A^T (L \otimes I_N) AW = \lambda A^T (D \otimes I_N) AW. \]

   Let the solutions of this equation are \( w_0,w_1,...,w_d \) and their corresponding eigenvalues are \( \lambda_0, \lambda_1,...,\lambda_d \). The final linear dimension reduction mapping is \( A_i \rightarrow y_i=A_i W \), where \( W=(w_0,w_1,...,w_d) \).

4.3 Classifier design

In this paper, the purpose is to evaluate the performance of the proposed dimension reduction algorithm, so the simple \( k \)-nearest neighbor classifier is used to complete the recognition. The \( k \)-nearest neighbor classifier is an important approach for non-parametric classification, its basic idea is:

Suppose the training set has \( c \) classes \( \omega_1, \omega_2, ..., \omega_c \), the number of each class is \( N_i \), \( i=1,2,...,c \). Calculate the Euclidean distance between the test sample \( y \) and the arbitrary train sample \( y' \):

\[ d_i' = \| y - y' \| \quad j = 1,2,...,N_i \]  \hspace{1cm} (11)

Where \( i \) represents the \( \omega_i \) class, \( j \) represents the \( j \)th sample of \( \omega_i \) class. Suppose the test sample \( y \) has \( k \) neighbors, the sample number of \( \omega_i \), \( \omega_2, ..., \omega_c \) class is \( k_1, k_2, ..., k_c \) respectively. Define the distinguish function:

\[ d_i(y) = k_i, i = 1,2,...,c \]  \hspace{1cm} (12)

If the \( k \) nearest algorithm has no threshold, and an arbitrary class satisfies:

\[ d_m(y) = \max_{i=1,2,...,c} d_i(y) \]  \hspace{1cm} (13)

Then \( y \) is considered belonging to the \( m \)th class. In other words, for an unknown sample \( y \), its \( k \) nearest neighbors are selected, and \( y \) is labeled the class of most neighbors. If the \( k \) nearest algorithm has threshold \( r \), suppose

\[ D = \min_{i=1,2,...,k} \| y - y_i \|, i = 1,2,...,k \]  \hspace{1cm} (14)

If \( D < r \), \( y \) is considered not belonging to any class, otherwise the class label of \( y \) can be determined by \( k \) nearest method.

5. Experimental results

5.1 Data preparation

In order to demonstrate the proposed scheme, we made a classification experiment using four kinds of ISAR images: F15, F16, Jian10 and “Jaguar”. These images are simulated based on high-frequency electromagnetic scattering theory[20] and stepped-frequency ISAR imaging principles [21-23].
The following radar parameters are selected: carrier frequency \( f_c = 9 \) GHz, stepped frequency step size \( \Delta f = 3 \) MHz, number of stepped frequency steps \( N = 64 \), number of pulses \( M = 256 \), pulse repetitive frequency \( f_p = 15 \) KHz.

Here, the ISAR images are generated from \(-45^\circ\) to \(45^\circ\) yaw angle \((0^\circ\) pitch and \(0^\circ\) roll), \(-45^\circ\) to \(45^\circ\) pitching angle \((0^\circ\) yaw and \(0^\circ\) roll), \(-45^\circ\) to \(45^\circ\) rolling angle \((0^\circ\) pitch and \(0^\circ\) yaw) respectively with a \(3^\circ\) interval, 8 different rotate rates and 15 different distances are used. Thus, the number of these ISAR images for each target is \(3600 \times 3\). These ISAR images are cut into \(N = 35\) in down-range direction and \(M = 100\) in cross-range direction. Figure 1 shows some of the ISAR images with different attitude angle, cross-range scale and position.

In this classification experiment, we select 600 samples randomly from F15, F16 and Jian10 respectively, yielding \(600 \times 3\) train samples, and the test set A is include 900 samples which are selected from the remainder ISAR images of F15, F16 and Jian10. The test set B has 300 samples from “Jaguar”, where the situation of rejection recognition is considered. As a result, the training set and test set are entirely different. The training set is used to learn the transformation matrix \( W \); test samples are mapped into the feature subspace with the transformation matrix, and then the \(k\)-nearest neighbor classifier is used to complete the recognition.

5.2 Experimental result

Table 1 shows the recognition results. We can see that the higher recognition rate is acquired with the feature space obtained by 2DLPP algorithm comparing to PCA, LDA and LPP. The recognition rate in original high-dimensional ISAR image space is represented as “Baseline”. In this simulation experimentation, the signal-to-noise ratio (SNR) of ISAR images is set to 10dB.

| Approach       | Dims | Recognition Rate |
|----------------|------|------------------|
| Baseline       | 3500 | 69.1%            |
| PCA            | 30   | 89.1%            |
| PCA+LDA        | 2    | 85.2%            |
| PCA+LPP        | 15   | 95.6%            |
| 2DLPP          | \(35 \times 6\) | 98.6%            |

5.3 Algorithm complexity analysis

In this paper, the algorithm complex of LPP and 2DLPP is also be analysed.
1) Create adjacent graph $G$: the algorithm complexity is $O(N^2+\log N)+O((N(N-1)/2)(m\times n))$. Where $m\times n$ is the pixel quantity of ISAR image, $N$ is the number of ISAR images.

2) Compute the weights:

(1) heat kernel: The algorithm complexity is $O(K \times N \times m \times n)$, where $k$ is the number of neighborhood.

(2) Simple-minded: In this case, the algorithm complexity is $O(k \times N)$.

3) Eigenmap:

(1) LPP: The algorithm complexity of $XLX^T$ is $O(m \times n \times (k + 1) \times N) + O((m \times n)^2 \times N)$; The algorithm complexity of $XDX^T$ is $O(m \times n \times N) + O((m \times n)^2 \times N)$; The algorithm complexity of calculating the translation matrix $W$ is $O(m \times n)^3$; The total algorithm complexity is $O(2mn \times mnN + m^3 n^3)$.

(2) 2DLPP:

The algorithm complexity of $A(L \otimes L_o)A^T$ is $O(m \times n \times (k + 1) \times N) + O((m \times n)(k + 1)) + O(m \times n \times (k + 1)^2)$; The algorithm complexity of $A(D \otimes L_o)A^T$ is $O(m \times n) + O(m \times n \times N) + O(m \times n \times (k + 1)^2)$; The algorithm complexity of calculating the translation matrix $W$ is $O((n)^3)$. The total algorithm complexity is $O(2N \times mnN + n^3)$.

Obviously, the algorithm complexity of LPP is much higher than 2DLPP.

6. Conclusion

In this paper, the idea of manifold learning is introduced into ISAR target recognition domain. Firstly, ISAR image subspace is obtained by 2D Locality Preserving Projections (2DLPP) algorithm, and then the $k$ nearest neighbor classifier is applied to complete the recognition. The proposed 2DLPP algorithm is based directly on 2D ISAR images rather than 1D vectors as conventional LPP does. The simulated experimental results suggested that 2DLPP has better classification performance comparing to PCA, LDA and LPP.

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