ISSN: 2350-0328

International Journal of Advanced Research in Science, Engineering and Technology

Vol. 3, Issue 7 , July 2016

The target HRRP recognition with supervised discrimination sparse neighbourhood preserving embedding

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ABSTRACT: In this paper, we combine the objective function of three methods together and propose a new method, called supervised discrimination sparse neighborhood preserving embedding (SDSNPE). The proposed method can preserve the local and global manifold structure of the samples simultaneously. In addition, the supervised information is introduced into the neighborhood preserving embedding (NPE) and sparse preserving projection (SPP), it not only can preserve the sparse reconstruction relationship between samples and also can use the discriminate information included in the sparse coefficients to help to achieve feature extraction. Finally, experiments on target HRRP samples demonstrate the effectiveness of our proposed method.

KEYWORDS: High resolution range profile, Neighborhood preserving embedding, Maximizing margin criterion, Sparse preserving projection.

I. INTRODUCTION

The ability to detect and locate targets on a day/night, all weather bases, over wide areas, has long made radar system a key sensor in many military and civilian applications. We find that the utility of the information supplied by a radar system would be hugely enhanced if targets could additionally be recognized. The HRRP is the amplitude of the coherent summations of the echoes from target scatters in each range cell, which represents the projection of target scattering centres on the radar line of sight (RLOS). It contains the target structure signatures, such as target size, scatter distribution, etc., Therefore, the target HRRP recognition has received intensive attention by the radar automatic target recognition (RATR) community [1]-[5]. The target HRRP is often confronted with very high-dimensional data, in order to avoid small sample size (SSS) problem and curse of dimensionality, feature extraction is performed before the recognition, which can reduce the dimensionality of HRRP greatly and the extracted features are expected to have the properties of effectiveness, robustness and feasibility with tolerable computational complexity.

As the three sensitivities and the influence of radar parameters and working environment, the HRRP is highly nonlinear [2][3], which makes the traditional linear methods not fit for the feature extraction of HRRP. The kernel function and manifold learning are two mainly studied nonlinear feature extraction methods [4][6]-[8]. Manifold learning assume the local samples can be represent as linear and then extend the local linear to the global linear under different function criterions. Although they can deal the sample nonlinear problem, the existing manifold learning methods can only preserve either the local or global manifold structure of the samples, can't preserve them simultaneously in the phase of feature extraction.

In this paper, we introduce the supervised information into NPE and SPP, which can preserve the sparse reconstruction relationship of the samples, and based on the objective function of three methods propose a new SDSNPE method, it not only can preserve the local and global manifold structure of the samples simultaneously, also can extract the nonlinear features of HRRP. Extensive experiments on three target HRRP datasets show that the performance of our method outperforms the others.

ISSN: 2350-0328

International Journal of Advanced Research in Science, Engineering and Technology

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II. REVIEW OF THE RELATED METHODS

A. The Neighborhood Preserving Embedding

NPE [6] is a linear approximation to the LLE [7], it aims at preserving the local manifold structure. The algorithmic procedure is mainly consists of four steps. Firstly, constructing a neighborhood graph G based on the k-nearest neighbor or the neighbor within ε radius. Secondly, computing the reconstruction weights, according to the adjacency graph G, every sample in training set is reconstructed by the linear combination of its weighted neighbors. Let W denote the weight matrix, the weight W_{ij}, the edge from node i to node j, can be computed by minimizing the following objective function

$$\sum_i \left\| x_i - \sum_{j \in \pi_k(x_i)} W_{ij} x_j \right\| \quad s.t. \sum_{j \in \pi_k(x_i)} W_{ij} = 1 \tag{1}$$

where $\pi_k(x_i)$ is the k nearest neighbors set of x_i. Thirdly, we fix the weight matrix W while optimizing the coordinates y_i. Suppose that there exists a linear transformation $y_i=u^T x_i$, where u is the basis vector, the basis vector u is computed by solving the minimization problem

$$U^* = \arg\min_U \frac{U^T X M X^T U}{U^T X X^T U} \tag{2}$$

where $M = (I-W)^T (I-W)$, $X = [x_1, x_2, ..., x_n] \in R^{m \times n}$ be the data matrix including all the training samples in its columns. The optimal u is given by the minimum eigenvalue solution to the following generalized eigenvalue problem

$$X M X^T u = \lambda X X^T u \tag{3}$$

Finally, the basis vectors $U = [u_1, u_2, ..., u_d]$ of the d-dimensional subspace correspond to the d smallest eigenvectors of the Eq. (3). The d-dimensional embedding is computed by the formulation $Y = U^T X$.

The NPE is an unsupervised dimensionality reduction algorithm; it can only preserve the local neighborhood structure of the data manifold and can't preserve the global structure of the data manifold. Moreover, the NPE can't find the discriminant structure in the sample space effectively.

B. The Sparse Preserving Projection

Sparse preserving projection (SPP) [9] is a method to design the weight matrix W straightforwardly based on the theory of sparse representation (SR). For the sake of the pages, here we don't review the concept of SR and in the reference [9] the method is discussed in details. The SR expect to reconstruct the sample x_i using as few samples as possible and the sparse reconstructive weight vector s_i for each sample x_i can be obtain through the following modified l_1 minimization problem

$$\hat{s}_i = \min_{s_i} \|s_i\|_1 \quad s.t. \quad \|x_i - X s_i\| < \varepsilon, \quad \sum_i s_i = 1 \tag{4}$$

where $s_i = [s_{i,1}, ..., s_{i,i-1}, 0, s_{i,i+1}, ..., s_{i,n}]^T$ is a n-dimensional vector in which the i-th element is equal to zero, implying that the x_i is removed from X, and the elements $s_{i,j}, i \neq j$ denote the contribution of each x_j to reconstructing x_i; the sum of all the elements in s_i is one. After computing the sparse weight vector $\hat{s}_i$ for each sample x_i, we can define the sparse reconstruction weight matrix S as $S = [\hat{s}_1, \hat{s}_2 ..., \hat{s}_n]^T$. The element $\hat{s}_i$ in S is not simple similarity measure between samples x_i and x_j, and in this sense S is essentially different from the weight matrix W in NPE. As the analysis in [9], the weight matrix S reflects some intrinsic geometric properties of the samples and discriminant information can be naturally preserved in weight matrix S. In order to preserve the characteristics in the embedding space, similar to NPE,

ISSN: 2350-0328

International Journal of Advanced Research in Science, Engineering and Technology

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defining the following objective function to seek the projections which best preserve the optimal weight vector $\hat{s}_i$.

$$\min_U \sum_{i=1}^{n} \left\| U^T x_i - U^T X \hat{s}_i \right\|^2 \quad (5)$$

With simple algebraic formulation and impose a constraint to avoid degenerate solutions, the objective function can be written as

$$\min_U \frac{U^T X (I - S - S^T + S^T S) X^T U}{U^T X X^T U} \quad (6)$$

The optimization problem boils down to a generalized eigenvalue problem like in NPE.

C. The Maximizing Margin Criterion

The MMC [10] based on a new feature extraction criterion; it can maximize the margin between classes and get better class separability. Moreover, it doesn't suffer the small size samples (SSS) problem, which is known to cause serious stability problems in linear discriminant analysis (LDA). Let c and n_i denote the number of classes and the number of samples in class i. The intuition of MMC is to maximize the distances between class means and minimize the within scatter of classes in the projected space. The between-class scatter matrix, within-class scatter matrix and the objective function are defined as follows

$$S_b = \sum_{j=1}^{c} n_i (m_i - m)(m_i - m)^T \quad (7)$$

$$S_w = \sum_{i=1}^{c} \sum_{j=1}^{n_i} (x_i^j - \overline{x}_i)(x_i^j - \overline{x}_i)^T \quad (8)$$

$$U = \arg\max_{U^T U = I} tr(U^T (S_b - S_w) U) \quad (9)$$

Note that the Eq. (9) may also use other constraints instead, For example, if we add the constraint $U^T S_w U = I$ and then maximize the $U^T S_b U$. It easy to see that with such a constraint, MMC in fact results in LDA. In order to keep the same with the constraint in the objective functions of the above two methods, and avoid the SSS problem. We define the constraint used here the same as in NPE and SPP. Through the objective function in Eq. (9), it easy to find the MMC only considering the global properties of the samples, it may lose the local geometric information of the samples and project the samples in an incorrect subspace.

III. SUPERVISED DISCRIMINATION SPARSE NEIGHBORHOOD PRESERVING EMBEDDING

As we know, the NPE and SPP are unsupervised methods with subspace learning characteristic, the information provided by the class labels of the training data can be used to guide the procedure of dimension reduction and describe the intrinsic structure of training data in low-dimensional space. Therefore, we introduce the supervised information into the NPE and SPP first and then propose a new objective function based on the objective functions of the above three methods. The supervised NPE has the same steps with NPE except the step of constructing the neighborhood graph G. Here, we only give out the analysis of how to construct the neighborhood graph. In original NPE, it selects the neighbors based on the distance between the sample x_i and x_j, we use the label information of the samples and select the neighbors x_j of data point x_i from the class that x_i itself belongs to. That is to say, the neighbors of a sample in per class will always be picked from that same class. Like the supervised NPE, we introduce the supervised information into SPP. In the supervised SPP, all the atoms used to sparse representation of x_i will always be picked from the same class with x_i, the sparse weight vector $\hat{s}_i$ is redefined as follows

$$\hat{s}_i = \min_{s_i} \|s_i\|_1 \quad s.t. \quad \|x_i - X_k s_i\| < \varepsilon, \; label(x_i) = k \;, \; \sum_i s_i = 1 \quad (10)$$

where X_k denotes all the samples in class k, $label(x_i) = k$ denotes the label of x_i is k. Next, we will analysis the scatter matrices under the view of normalized graph Laplacian [12]. The total scatter matrix is equal to the sum of

ISSN: 2350-0328
International Journal of Advanced Research in Science, Engineering and Technology
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between-class scatter matrix and within-class scatter matrix

$$S_t = S_b + S_w = X(I - \frac{1}{n}e)e^T X^T \tag{11}$$

where I is identity matrix and e is a column vector and each of its entry takes the value one. If the weight matrix of a graph is denoted as M, the normalized graph Laplacian is defined as $L = D^{-1/2}(D-M)D^{-1/2}$,where D is a diagonal matrix with its entries being the row sums of M, i.e., $D_{ii} = d_i$ and $d_i = \sum_j M_{ij}$ is the degree of vertex x_i. Then the scatter matrix can be rewritten as $S = XLX^T$. So, in this normalized graph Laplacian view, the scatter matrices S_t, S_w and S_b can be redefined by the corresponding weight matrices M_t, M_w and M_b, Laplacian matrices L_t, L_w and L_b. The M_t is defined as $(M_t)_{ij} = 1$ for all the samples. $(M_w)_{ij} = 1$ if x_i and x_j belong to the same class; 0, otherwise. $(M_b)_{ij} = 1$ if x_i and x_j belong to the different classes; 0, otherwise. Since the graph Laplacian of the between-class scatter matrix is

$$\begin{aligned} L_b &= D_t^{-1/2} A_t D_t^{-1/2} - D_w^{-1/2} A_w D_w^{-1/2} \\ &= D_b^{-1/2}(D_b - A_w)D_b^{-1/2} \end{aligned} \tag{12}$$

where the definition of D_w, D_b and D_t are similar with D, they are corresponding to the diagonal degree matrices. In summary, the objective function of MMC in Eq. (9) can be written as

$$\begin{aligned} & tr(U^T(S_b - S_w)U) \\ &= tr(U^T(S_t - 2S_w)U) \\ &= tr(U^T X(L_t - 2L_w)X^T U) \end{aligned} \tag{13}$$

To avoid degenerate solutions, we add the constraint to the Eq. (13), and the final form of the objective function defined as

$$U^* = \arg\max_U \frac{tr(U^T X(L_t - 2L_w)X^T U)}{tr(U^T XX^T U)} \tag{14}$$

The optimization problem boils down to a generalized eigenvalue problem like in NPE.

Under the supervised condition, we assume that there exist a transform U, it can satisfy the Eq. (2), (6) and (14) simultaneously. So, when projecting the samples, it can makes the samples separated between classes and compacted within class; preserves the local and global manifold structure of the sample at the same time. In addition, the sparse coefficients in Eq. (10) can preserve the sparse reconstruction relationships between samples and include discrimination information of the samples. Based on this assumption, we combine the objective functions of NPE, MMC and SPP together and propose the supervised discrimination sparse neighborhood preserving embedding (SDSNPE) algorithm, its objective function defined as follows

$$\begin{cases} \min \ tr(U^T XMX^T U) \\ \min \ tr(U^T XS_\alpha X^T U) \\ \max \ tr(U^T X(L_t - 2L_w)X^T U) \end{cases}$$
$$s.t. \ U^T XX^T U = I \tag{15}$$

The essence of the above optimization problem is to find a transformation to project the data into a subspace, in which the sparse characteristic and the similarity between samples are maintained. Moreover, the transformation separated the samples from different class and made the samples compact in the same class. The above optimization problem can be equivalent to the following form

$$\begin{aligned} & \min_U U^T(\gamma XM_\alpha X^T + \beta XS_\alpha X^T - (1-\beta-\gamma)X(L_t - 2L_w)X^T)U \\ & s.t. \ \ U^T XX^T U = I \end{aligned} \tag{16}$$

where $M_\alpha = W + W^T + W^T W$, $S_\alpha = S + S^T + S^T S$ and $\gamma > 0$, $\beta > 0$, $\gamma + \beta \in (0,1)$ control the amount of sparse reconstruction, global structure and local structure. Using the Lagrange multiplication, the optimal basis vector u is

ISSN: 2350-0328
International Journal of Advanced Research in Science, Engineering and Technology
Vol. 3, Issue 7 , July 2016

given by the maximum eigenvalue solution to the following generalized eigenvalue problem

$$(\gamma XM_{\alpha}X^{T}+\beta XS_{\alpha}X^{T}-(1-\beta-\gamma)X(L_{t}-2L_{w})X^{T})u=\lambda XX^{T}u \tag{17}$$

The transformation matrix U is composed of the d largest eigenvectors of the Eq. (17), $U=[u_1,u_2,...,u_d]$. In Eq. (16), we can also write the objective function as the problem of solving the minimum value, however, when solve the generalized eigenvalue problem, seeking the maximum eigenvalue is more stable than seeking the minimum eigenvalue.

IV. EXPERIMENTAL RESULT

In this section, we carry out experiments on millimeter wave radar HRRP. In order to demonstrate the effectiveness of the proposed method, we compare the SDSNPE with NPE, LPP [13], MMC, SNPE and SPP, the classifier we used is k nearest neighbor classifier. The experimental environment is set as follows. According to the geometric model of the real target, corner reflectors with different positions are utilized as the scattering center models to simulate three different kinds of targets and the stepped frequency radar is used to get the HRRP of targets. For each target, we obtain a 256 point HRRP with the azimuth from 0° to 179.5° interval 0.5° and the elevation angle constantly is 30°. Thus, each target is comprised of 360 HRRP samples and each sample has 256 features. Let all the samples alignment with target geometric center and l_2 normalization are applied to overcome the time-shift, amplitude sensitivities at first. We select 70,75,80,...,120 labeled samples equally interval from each target HRRP dataset as training set respectively, and select 120 samples from the rest of each HRRP dataset as testing set randomly. The average recognition rate of 20 tests is utilized to measure the performance of each algorithm. The recognition rate curves are shown in Figure 1.

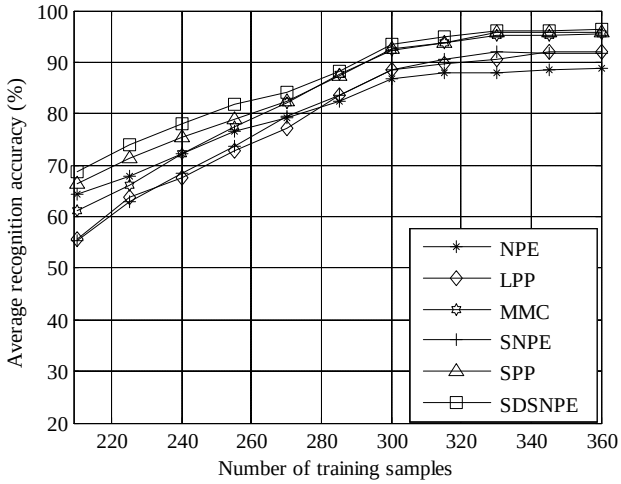

Figure 1 The performance comparison of recognition rate

As can be observed from Figure 1, the proposed SDSNPE achieve the best recognition rate under all the number of training samples. The advantage of the proposed algorithm is obvious, especially when the training samples less than 270. When the training samples are 360, the SDSNPE reach the highest, 96.28%, about 0.5% higher than SPP and 0.8% higher than MMC, the performance of SPP and MMC are similar after the training samples more than 270. In order to test the anti-noise performance of the proposed method, we get the noise clutter from the grass, concrete and soil background respectively, and add the clutters into the HRRP samples. The number of training sample is 360 and testing sample is 360, the parameters are consistent with the above experiment and the average recognition rate and the stand deviations are shown in Table 1.

From the data in Table 1, in the clutter background, the recognition rate of SDSNPE, 81.88%, is still the highest; the worst is NPE, about 75.92%. Under the grass background, the performances of all methods are poor and under the concrete background, the performances of all methods are highest. In addition, the performances of SNPE and SPP, which based on the sparse coefficient to reconstruct the samples, are higher than the NPE and LPP, which based on the k near neighbors to reconstruct the samples. That is to say, the sparse coefficient is more effective than the k near neighbor to preserve the structure and reconstruction relationship of the samples. The proposed SDSNPE has the

ISSN: 2350-0328
International Journal of Advanced Research in Science, Engineering and Technology
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advantage of SPP, MMC and NPE simultaneously, so the average recognition rate is higher than SPP.

Table 1 The recognition accuracy under different background clutters

Method	Grass	Concrete	Soil	Average
NPE	72.36±10.9	79.17±7.4	76.23±9.8	75.92
LPP	75.87±6.3	79.96±4.2	77.52±3.1	77.79
MMC	75.23±4.1	85.79±2.6	82.73±3.1	81.25
SNPE	73.64±5.3	80.28±4.7	78.59±4.9	77.50
SPP	72.32±5.6	81.43±4.8	79.88±4.5	77.88
SDSNPE	80.26±3.3	83.19±2.7	82.20±3.0	81.88

V. CONCLUSIONS

In this paper, based on the similarity of three objective functions, we introduce the supervised information into the methods and propose a manifold based feature extraction algorithm, called SDSNPE, to extract the features that can best preserve the local, global manifold structure of samples and the sparse reconstruction relationship between samples.

The experiments result on three radar target HRRP show that the SDSNPE method not only has a better recognition performance than the contrast methods, but also better robustness to clutter noise.

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ISSN: 2350-0328

International Journal of Advanced Research in Science, Engineering and Technology

Vol. 3, Issue 7 , July 2016

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