DIMENSIONALITY REDUCTION BASED ON MAXIMUM MARGIN LOCAL SCALING CUT FOR POLSAR IMAGE CLASSIFICATION

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Abstract: Thanks to the high radar resolution, land-cover classification is one of the most significant applications for PolSAR images. Apart from the selection of classifiers, the suitable features also have a great influence on classification results and efficiency. This paper proposes a noval supervised dimensionality reduction method called Maximum Margin Local Scaling Cut (MMLSC).

Let us assume that the training set is $X = (x_1, x_2, \cdots, x_l) \subset \Re^{D\times l}$ and includes c classes. We focus on finding a transformation $y = P^T x$ to preserve discriminant properties from D dimensionality to d dimensionality ($d < D$).

Based on the thought of normalized cut, we define the inter-class dissimilarity matrix and within-class dissimilarity matrix,

$$C_p = \sum_{i\in V_p} \sum_{j\in \bar{V}_p} \frac{1}{n_p n_{c(j)}} (x_i - x_j)(x_i - x_j)^T \tag{4}$$

$$A_p = \sum_{i\in V_p} \sum_{j\in V_p} \frac{1}{n_p n_p} (x_i - x_j)(x_i - x_j)^T \tag{5}$$

and normalized cut can be rewritten as

$$Ncuts(P) = \sum_{p=1}^{c} \frac{\left|P^T C_p P\right|}{\left|P^T A_p P + P^T C_p P\right|} \tag{6}$$

Because here normalized cut is nonlinear function, we use its linear form, which is named scaling cut.

$$Scuts(P) = \frac{\left|\sum_{p=1}^{c} P^T C_p P\right|}{\left|\sum_{p=1}^{c}(P^T A_p P + P^T C_p P)\right|} = \frac{\left|P^T \sum_{p=1}^{c} C_p P\right|}{\left|P^T \sum_{p=1}^{c}(A_p + C_p)P\right|} = \frac{\left|P^T C P\right|}{\left|P^T (A+C)P\right|} \tag{7}$$

In this paper, we change two points in (7):

1) In order to reduce the computational complexity and preserve manifold local information, inter-class and within-class embedded graph are first constructed based on K-Nearest Neighbor algorithm, and then only inter-class and within-class neighbor points participate in the computation of C_p and A_p, then C and A in (7) change into

$$C = \sum_{p=1}^{c}\sum_{i=1}^{n_p}\sum_{j=1}^{l} N_{ij}^{b}(x_i - x_j)(x_i - x_j)^T,\ N_{ij}^{b} = \begin{cases} 1/n_p q_b, x_j \in N_b(x_i) \\ 0 \qquad ,otherwise \end{cases} \tag{8}$$

$$A = \sum_{p=1}^{c}\sum_{i=1}^{n_p}\sum_{j=1}^{l} N_{ij}^{w}(x_i - x_j)(x_i - x_j)^T,\ N_{ij}^{w} = \begin{cases} 1/n_p q_w, x_j \in N_w(x_i) \\ 0 \qquad ,otherwise \end{cases} \tag{9}$$

2) Based on Maximum Margin Criterion (MMC), we proposes a new feature extraction criterion to replace (7)

$$\begin{cases} \max tr(P^T (C - A)P) \\ s.t.\ \ P^T P = I \end{cases} \tag{10}$$

The formula above ensures dissimilarity between classes is large and within classes is small, then the constraint ensures projection vectors are orthogonal.

To solve the above optimization problem, we use Lagrange multiplier method. After derivation, it is equivalent to solving the eigenvectors in (11) which the first d maximum eigenvalues correspond to.

$$(C - A)P = \lambda P \tag{11}$$

So we can claculate the transformation matrix P from equation (11), and get the new samples in low-dimensional space.

Later, we use the experiment dataset acquired by the C-band AIRSAR system in Flevoland to test our algorithm. We apply totally 56 polarimetric features including the parameters from different decomposition methods, correlation coefficients and reflectivity ratios among three polarization channels on linear basis and circle basis.

After dimensionality reduction by several methods, we apply K-Nearest Neighbor (K=1) classifier to classify this PolSAR image. When the training samples number of each class is 10, 14, 18, 22, 26 and 30, the best classification accuracies based on different dimensionality reduction methods are that LDA: 70.52%, 73.91%, 77.93%, 78.82%, 79.09%, 81.10%; FLDA: 72.23%, 74.69%, 78.33%, 79.24%, 79.91%, 81.74%; LSC: 68.58%, 72.86%, 78.72%, 79.01%, 80.71%, 81.12%; MMLSC: 75.03%, 77.57%, 79.64%, 80.70%, 81.84%, 82.84%. We can easily find our method (MMLSC) is a good dimensionality reduction method.

Keyword: PolSAR, Feature Extraction, Scaling Cut, Maximum Margin Criterion, Classification