Hyperspectral Image Classification Based on Dimensionality-Reduced Gabor Features and Decision Fusion (Postprint)

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Abstract

To address the problem that traditional hyperspectral image classification algorithms ignore spatial features, this paper proposes a hyperspectral image classification algorithm based on Gabor features and decision fusion. First, adjacent and highly correlated spectral bands are intelligently grouped via a coefficient correlation matrix; subsequently, Gabor features are extracted from each group within the PCA projection subspace to quantify local directional and scale characteristics; then, locality-preserving non-negative matrix factorization is employed to reduce the dimensionality of these feature subspaces; finally, Gaussian mixture model classification is applied to the dimensionality-reduced features, and the classification results are merged using a logarithmic opinion pool decision fusion rule. Experimental results indicate that the proposed algorithm outperforms a total of eight state-of-the-art classification algorithms, encompassing both traditional and existing approaches.

Full Text

Preamble

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Hyperspectral Image Classification Based on Dimensionality-Reduced Gabor Features and Decision Fusion

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Abstract: Traditional hyperspectral image classification algorithms often neglect spatial features. To address this limitation, this paper proposes a novel hyperspectral image classification algorithm based on Gabor features and decision fusion. First, adjacent and highly correlated spectral bands are intelligently grouped using a coefficient correlation matrix. Next, Gabor features are extracted from each group within a PCA projection subspace to quantify local directional and scale characteristics. Then, locality-preserving non-negative matrix factorization is employed to reduce the dimensionality of these feature subspaces while preserving local structure. Finally, a Gaussian mixture model classifier is applied to the reduced-dimensional features, and classification results are merged using a logarithmic opinion pool decision fusion rule. Experimental results demonstrate that the proposed algorithm outperforms eight traditional and state-of-the-art classification methods.

Keywords: hyperspectral image; classification; Gabor features; Gaussian mixture model; decision fusion; PCA projection

0 Introduction

Hyperspectral images (HSI) record hundreds of spectral bands for each pixel, providing high spectral resolution and enhanced potential for robust image classification [1,2]. However, this high dimensionality degrades the generalization capability of statistical classifiers, such as maximum likelihood estimators based on Gaussian class-conditional statistics [3]. Consequently, dimensionality reduction algorithms are typically required to project HSI data into lower-dimensional spaces, including conventional principal component analysis [4], Fisher linear discriminant analysis (LDA) [5], and numerous variants of these methods.

Li et al. [6] proposed a hyperspectral image classification method based on Gaussian mixture models and Markov random fields, employing locality-preserving non-negative matrix factorization and local Fisher discriminant analysis as preprocessing steps to reduce data dimensionality for the Gaussian mixture model classifier while preserving multimodal structures within the data. Kuo et al. [7] developed a kernel-based feature selection method for RBF kernel SVM classification of hyperspectral images, enabling both feature subset selection and feature ranking based on computed coefficient magnitudes. Since SVM is insensitive to HSI dimensionality and Markov random fields can capture complex spatial contextual information, SVM-MRF frameworks have been applied to HSI classification.

Additional HSI classification approaches include local binary patterns, sparse representation, and machine learning methods. Li et al. [8] utilized local binary patterns to extract local image features, employing both feature-level and decision-level fusion of these features with an extreme learning machine classifier. Zhang et al. [9] proposed a nonlocal weighted joint sparse representation classification method that outperforms other sparsity-based algorithms and classical

SVM approaches. Liang and Li [10] exploited sparse representation of deep learning features for remote sensing image classification, using convolutional neural networks to extract deep features from high-level image data within a sparse representation classification framework. Tao et al. [11] applied stacked sparse autoencoders for spatial feature learning in hyperspectral image classification, enabling adaptive learning of appropriate feature representations from unlabeled data.

Li and Du [12] demonstrated that two-dimensional Gabor features extracted in PCA projection subspaces are effective for HSI classification. Ye et al. [13] proposed two fusion classification algorithms based on Gabor features and derivative features to achieve superior HSI classification performance. Jia et al. [14] introduced a collaborative representation method based on three-dimensional Gabor features for HSI classification, which reduces computational complexity.

This paper investigates existing hyperspectral image classification methods and proposes a novel algorithm based on Gabor features and decision fusion that considers both original spectral and spatial characteristics. The method intelligently groups correlated spectral bands, extracts Gabor features from each group in PCA projection subspaces, reduces spatial feature dimensionality, and finally merges Gaussian mixture model classification results using decision fusion rules to achieve hyperspectral image classification.

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1 Proposed Classification Method

The correlation coefficient matrix is used to group spectral bands, and Gabor textures within the PCA projection subspace are employed to extract spatial-spectral features. Following feature extraction, locality-preserving non-negative matrix factorization (LPNMF) reduces the dimensionality of feature subspaces. Subsequently, a Gaussian mixture model (GMM) classifier is applied, and a logarithmic opinion pool (LOGP) decision fusion method merges all classification results. This classification fusion system is designed for hyperspectral image classification tasks, with the overall process illustrated in [Figure 1: see original paper].

Partitioned subspaces provide increased class separability while minimizing statistical dependencies between subspaces. For example, the Indian Pines dataset (with 220 bands) naturally partitions into five groups corresponding to five light-colored blocks residing on the diagonal of the CCM, as shown in [Figure 2: see original paper]. Within each group, bands are highly correlated with one another. Since spectral bands {104-108} and {150-163} represent water absorption bands, these bands are removed.

1.1 Band Selection

Hyperspectral images are partitioned into contiguous groups using the correlation coefficient matrix (CCM). Let $f(x, y)$ denote the original hyperspectral image and $g(x, y)$ denote the ground truth image. The cross-correlation function is defined as:

$$\langle\langle MATH_0 \rangle\rangle$$

where M and N represent the number of rows and columns, respectively, $\bar{f}$ is the mean of $f(x, y)$, and $\bar{g}$ is the mean of $g(x, y)$.

In the proposed fusion classification system, each bandpass is first considered, and system parameters are optimized to obtain optimal classification results. [Figure 3: see original paper] presents the overall classification accuracy (OA) for different parameter combinations of δ_{bw}, ψ, and PC (number of principal components). The optimal values for δ_{bw} and PC are observed to be 65 and 3, respectively. These parameters are selected for the proposed classification algorithm, as the parameter ψ exhibits low sensitivity to classification performance.

1.2 Gabor Transform

Gabor filters, consisting of sinusoidal functions modulated by a Gaussian envelope, can be regarded as orientation-dependent bandpass filters that effectively capture directional and scale characteristics of physical structures for HSI spatial feature extraction. However, HSI contains substantial spectral information across a wide spectral range with relatively small wavelength intervals, increasing processing complexity and statistical ill-conditioning in classification tasks. To improve efficiency, this paper considers dimensionality reduction prior to Gabor feature extraction. Since Gabor features extracted in PCA projection feature spaces have proven to yield excellent results, this dimensionality reduction strategy is adopted in the feature extraction process.

In two-dimensional coordinates, Gabor filters (including real and imaginary parts) can be expressed as:

$$\langle\langle MATH_1 \rangle\rangle$$

where λ represents the wavelength of the sinusoidal factor, ψ is the phase offset, γ is the spatial aspect ratio (default value set to 0.5 in the literature [10]), σ specifies the standard deviation of the Gaussian envelope determined by δ_{bw} and spatial frequency bandwidth, and θ represents the orientation separation angle between Gabor kernels. The parameters a' and b' are defined as:

$$\langle\langle MATH_2 \rangle\rangle$$

This formulation returns the real and imaginary parts of the Gabor filter.

1.3 Locality-Preserving Non-Negative Matrix Factorization

LPNMF combines the advantages of non-negative matrix factorization (NMF) and locality-preserving projection (LPP), resulting in parts-based representations using only additive operations where intrinsic geometric structure is preserved in the embedding space. These advantages enable successful dimensionality reduction for HSI. Additionally, LPNMF combined with GMM classifiers can achieve high-accuracy HSI classification.

The objective function of LPNMF is:

$$\langle\langle MATH_3 \rangle\rangle$$

where λ is a regularization parameter. The first term represents the standard objective function of non-negative matrix factorization using Kullback-Leibler divergence between X and UV. The second term enforces a geometric locality constraint between points in the reduced-dimensional subspace.

Here, W is an edge weight matrix measuring distances between points in the original space X, which follows LPP theory to preserve the inherent geometry of data distribution. The following multiplicative update rules are used to minimize the function and estimate matrices U and V:

$$\langle\langle MATH_4 \rangle\rangle$$

1.4 Gaussian Mixture Model and Decision Fusion

A Gaussian mixture model can be viewed as a combination of two or more Gaussian distributions. In a typical GMM representation, the probability density function $p(X)$ is expressed as a sum of K Gaussian components:

$$\langle\langle MATH_5 \rangle\rangle$$

where α_k represents the mixture weight for the k-th Gaussian component, and $N(X|\mu_k, \Sigma_k)$ denotes the Gaussian distribution with mean μ_k and covariance Σ_k, parameterized by vector $\Theta_k = \{\alpha_k, \mu_k, \Sigma_k\}$. Once the optimal number of components K is determined, iterative optimization strategies estimate the mixture model parameters.

This research employs Gabor features within a decision fusion system context. A multiple classifier system followed by decision fusion addresses the small sample size problem and ensures robust recognition of grouped bands. The logarithmic opinion pool (LOGP) classification strategy is investigated, which requires individual posterior probabilities $p_i(w_j|x)$ from each classifier to estimate global class membership:

$$\langle\langle MATH_6\rangle\rangle$$

where α_i represents the confidence score of the i-th classifier, w_j is the class label, i is the classifier index, and C is the number of classifiers detecting class j within the classifier ensemble.

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2 Experimental Results and Analysis

The experimental dataset is the Indian Pines hyperspectral remote sensing dataset, collected by NASA’ s Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor. This dataset represents a vegetation classification scene with 145×145 pixels and 220 spectral bands at a 20m spatial resolution. The original Indian Pines dataset includes 16 land cover categories, some containing few samples. Since probability distributions obtained from such small training samples cannot adequately represent their statistical characteristics, this paper selects an eight-class subset with sufficient pixels. For this dataset, an average of 50 training samples and 8624 test samples per class (a test-to-training ratio of approximately 21.6:1) are used for experiments. All simulations are implemented in MATLAB 2013a on a laptop with 250GB memory, an i7 processor, and Windows 10 operating system.

To quantify the effectiveness of the proposed algorithm, comparisons are made against eight other methods: traditional SVM, SVM-Markov Random Field (SVM-MRF), Local Fisher Discriminant Analysis-Gaussian Mixture Model (LFDA-GMM), locality-preserving non-negative matrix factorization-GMM (LPNMF-GMM), Local Fisher Discriminant Analysis-GMM-Markov Random Field (LFDA-G-MRF), locality-preserving non-negative matrix factorization-GMM-Markov Random Field (LPNMF-G-MRF), Decision Fusion GMM-Local Fisher Discriminant Analysis (DG-LFDA), and Decision Fusion GMM-locality-preserving non-negative matrix factorization (DG-LPNMF). [Figure 4: see original paper] presents classification results for different algorithms on the hyperspectral data.

The visual results demonstrate that the proposed algorithm achieves the best hyperspectral image classification performance, surpassing the other eight algorithms. This is attributed to the algorithm’s ability to preserve local information from adjacent features and the multimodal structure of hyperspectral images, resulting in visually superior classification maps.

provides the overall classification accuracy (OA) and Kappa coefficient results, averaged over 20 experimental runs. The proposed algorithm achieves an OA of 99.22%, approximately 22% higher than traditional SVM, 11% higher than SVM-MRF, and 4% higher than DG-LPNMF. The Kappa coefficient reaches 0.9907, which is 0.414 higher than LFDA-GMM, 0.3101 higher than LPNMF-GMM, and 0.257 higher than SVM. Both OA and Kappa values, along with their standard deviations, represent optimal performance, confirming that the proposed method outperforms the eight existing algorithms for hyperspectral image classification.

[Figure 5: see original paper] illustrates the relationship between training sample size and classification accuracy. The results show that the proposed algorithm is less sensitive to training sample quantity, with only modest OA improvements as training samples increase. In contrast, LFDA-G-MRF exhibits the greatest sensitivity to training sample size, showing substantial OA improvement with increased samples. Moreover, the proposed algorithm consistently achieves higher OA values across different training sample sizes, producing clearer and smoother classification maps that validate its effectiveness.

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3 Conclusion

This paper proposes a hyperspectral image classification algorithm based on Gabor features and Gaussian mixture models with decision fusion, addressing the limitation of traditional methods that consider only spectral features while neglecting spatial characteristics. The algorithm first groups correlated spectral bands using a correlation coefficient matrix, then extracts Gabor textures from each group, performs dimensionality reduction while preserving local structure, and finally merges classification results from Gaussian mixture models using decision fusion rules. Experimental results demonstrate superior performance compared to existing algorithms, achieving high OA values even with small sample sizes and producing clearer, smoother classification maps.

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Note: Figure translations are in progress. See original paper for figures.