On Combining Multiple Features for Hyperspectral Remote Sensing Image Classification

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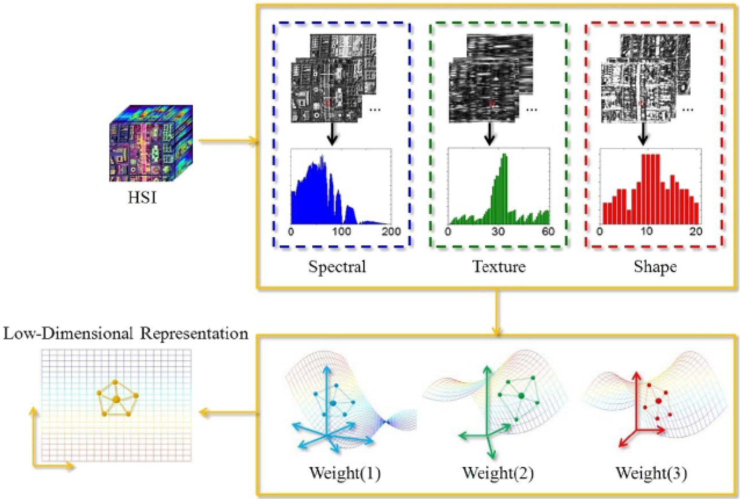
Outline

Introduction I

- They introduce the **patch alignment framework** to linearly combine multiple features in the optimal way and obtain a unified low-dimensional representation of these multiple features for subsequent classification.
- The proposed multiple feature combining (MFC) is based on manifold learning and a patch alignment framework.

Outline

MFC Framework



MFC Framework I

Two main components:

- In the first step, three kinds of features of HSI are introduced.
- Then, the MFC algorithm, which finds the particular contribution of each feature to the unified representation, is employed to obtain the final lowdimensional representation.

Multiple Feature Extraction I

Three kinds of features are introduced to the MFC. Each feature is represented as a single vector $v \in R^L$.

- *Spectral Feature:*

$$v_{\text{Spectral}} = [v_1, v_2, \ldots, v_l]^{\mathrm{T}} \in R^l$$

in which v_k denotes the DN in band k.

Texture Feature: Method to extract the texture feature based on 3D Gabor filters:

- $$G_{s,d}(x,y) = G_{\vec{\kappa}}(\overline{x}) = \frac{\|\vec{\kappa}\|}{\delta^2} \cdot e^{-\frac{\|\kappa\|^2 \cdot \|\overline{x}\|^2}{2\delta^2}} \cdot \left[e^{i \cdot \vec{\kappa} \cdot \overline{x}} - e^{-\frac{\delta^2}{2}} \right] \quad (2)$$

$$F_{s,d}(x,y) = G_{s,d}(x,y) * I(x,y).$$

The texture feature of a pixel (x,y) is obtained by

- $$v_{\text{Texture}} = [F_{1,1}(x,y), \ldots, F_{s,d}(x,y)]^{\mathrm{T}} \in R^{sd}.$$

Multiple Feature Extraction I

- Shape Feature: the pixel shape index method (PSI):
  - Step 1) Extension of direction lines: We define the pixel homogeneity of the ith direction by $PH_i = \|v^c - v^s\|^2$ where vc and vs are the spectral features of the central and surrounding pixels, respectively.

    The ith direction line is extended from the central pixel if the following statements are true:

    1) PHi is less than T1,

    2) the total number of pixels in this direction is less than T2.

    T1 is the threshold for homogeneity and pertains to the spectral variability in a local area. T2 is related to the average size of a shape area.

Multiple Feature Extraction II

- Step 2) Length of direction line: The PSI in the ith direction is calculated by the length of the direction line d_i. Then, the shape feature is achieved by $v_{\text{Shape}} = [d_1, d_2, \ldots, d_p]^{\mathrm{T}} \in R^p$

MFC I

In this framework, the proposed MFC algorithm finds a low-dimensional representation $Y = [y_1, y_2, \ldots, y_N] \in R^{d \times N}$ of features $\{V_{(i)} = [v_{(i)1}, v_{(i)2}, \cdots, v_{(i)N}] \in R^{L_i \times N}\}_{i=1}^{m}$, in which m is the number of features ($m = 3$; e.g., spectral, texture, and shape features) and N is the number of samples.

MFC I

1. Single Feature-Based Dimensional Reduction:

$$W(i,j) = \exp\left(-\|v_i - v_j\|^2/t\right)$$

$$\arg\min_{Y} f = \mathrm{tr}(YMY^{\mathrm{T}})$$
$$\text{s.t. } YY^{\mathrm{T}} = I$$

where $M \in R^{N\times N}$ is the alignment matrix of input samples, which could be computed by

$$M = D - W \tag{9}$$

MFC II

$$D_{ii} = \sum_{j=1}^{N} W(i, j).$$

1. Formulation of MFC:

$$\underset{Y,\omega}{\arg\min} f = \sum_{i=1}^{m} \omega_i^r \operatorname{tr}\left(Y M_{(i)} Y^{\mathrm{T}}\right)$$

$$\text{s.t. } YY^{\mathrm{T}} = I \quad \omega_i > 0 \quad \sum_{i=1}^{m} \omega_i = 1.$$

MFC I

- An alternating optimization is adopted to acquire a local optimal solution by iteratively updating Y and ω.

a) Fix ω to update Y. Optimization (13) is equivalent to

$$\arg\min_{Y} \operatorname{tr}(YMY^{\mathrm{T}}) \text{ s.t. } YY^{\mathrm{T}} = I \tag{14}$$

in which

$$M = \sum_{i=1}^{m} \omega_i^r M_{(i)}. \tag{15}$$

MFC II

b) Fix Y to update ω. The Lagrangian function for optimization (13) is

$$L(\omega, \lambda) = \sum_{i=1}^{m} \omega_i^r \operatorname{tr}\left(Y M_{(i)} Y^{\mathrm{T}}\right) - \lambda \left(\sum_{i=1}^{m} \omega_i - 1 \right) \tag{16}$$

with multiplier λ. Then, we obtain the partial derivative of $L(\omega, \lambda)$

$$\begin{aligned} \partial L / \partial \omega_i &= 0 \rightarrow r \omega_i^{r-1} \operatorname{tr}\left(Y M_{(i)} Y^{\mathrm{T}}\right) - \lambda = 0 \\ \partial L / \partial \lambda &= 0 \rightarrow \sum_{i=1}^{m} \omega_i - 1 = 0. \end{aligned} \tag{17}$$

Then, we find the global optimal ω by the solution of (17)

$$\omega_i = \frac{\left(1/\operatorname{tr}\left(Y M_{(i)} Y^{\mathrm{T}}\right)\right)^{1/(r-1)}}{\sum_{i=1}^{m} \left(1/\operatorname{tr}\left(Y M_{(i)} Y^{\mathrm{T}}\right)\right)^{1/(r-1)}}. \tag{18}$$

MFC I

Algorithm 1. The procedure of the MFC framework.

Input: A hyperspectral remote sensing image.

Method:

a) Extract multiple features $V = \{V_{(i)} \in R^{L_i \times N}\}_{i=1}^{m}$ from HSI by (1), (4), and (6).
b) Construct the feature matrix $X = \{X_{(i)} \in R^{L_i \times n}\}_{i=1}^{m}$ using a subset of samples.
c) Calculate an alignment matrix $M_{(i)}$ for each feature by (9) based on $X_{(i)}$.
d) Initialize $\omega = [1/m, 1/m, \ldots, 1/m]$.
e) Repeat
   Compute Y by optimization (14);
   Compute ω by equation (18);

   Until convergence.
f) Compute linear projection matrix U by (21).
g) Compute a low-dimensional feature representation of HSI: $V_{MFC} = U^{\mathrm{T}} V$.

Output: A low-dimensional MFC of the input HSI.

Computational Complexity of MFC I

- The computational complexity of the proposed approach is $O(n^3)$.
- The adopted linearization of MFC is effective in achieving the accuracy of the manifold learning and, at the same time, in reducing the computational cost.

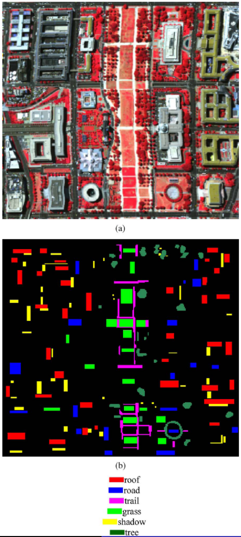
Outline

Experiments

Two hyperspectral data sets:

- The hyperspectral digital imagery collection experiment (HYDICE) airborne data over a Mall in Washington DC.
    - 210 bands, 0.4–2.4-μm. 1280 scan lines, with 307 pixels in each scan line. subset of the whole set, 280 $\times$ 307 p.
- Airborne data set by the Data Fusion Technical Committee of the IEEE Geoscience and Remote Sensing Society.
    - urban test area of Pavia. Size 1400x512, 1.3 m per pixel.

Experiments



Experiments

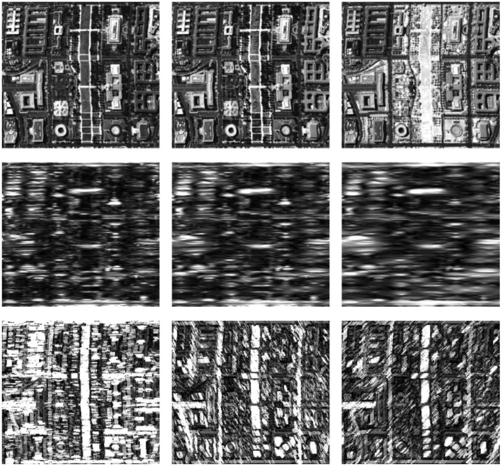
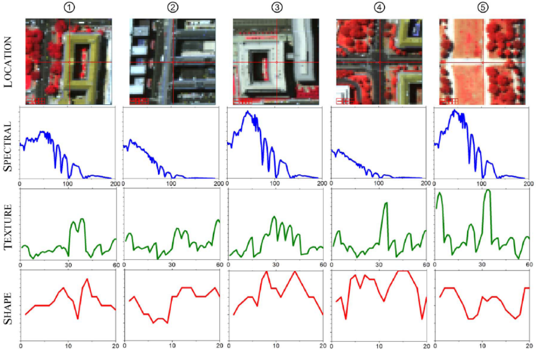


Fig. 3. Multiple features of the DC data set. (First row) Spectral feature images in band 36, 52, and 65. (Second row) Gabor texture feature images, with $d = 1$ and $s = 1, 3,$ and 5, respectively. (Third row) Shape feature images in d1, d8, and d16, respectively.

Experiments



SPECTRAL FEATURE

	①	②	③	④	⑤
①	1	0.89	0.98	0.86	0.98
②	0.89	1	0.86	0.99	0.85
③	0.98	0.86	1	0.81	0.99
④	0.86	0.99	0.81	1	0.80
⑤	0.98	0.85	0.99	0.80	1

(a)

TEXTURE FEATURE

	①	②	③	④	⑤
①	1	0.62	0.46	0.61	0.48
②	0.62	1	0.08	0.59	0.39
③	0.46	0.08	1	0.25	0.15
④	0.61	0.59	0.25	1	0.72
⑤	0.48	0.39	0.15	0.72	1

(b)

SHAPE FEATURE

	①	②	③	④	⑤
①	1	0.05	0.74	0.48	0.36
②	0.05	1	0.02	0.21	0.31
③	0.74	0.02	1	0.66	0.52
④	0.48	0.21	0.66	1	0.60
⑤	0.36	0.31	0.52	0.60	1

(c)

Fig. 4. Complementary properties of multiple features for different pixels in the DC data set.

Classification Result

To compare the effectiveness of the proposed MFC with the conventional dimension reduction methods, we show the performance of the supervised classification results of the following methods:
1) best feature: the best performance of the singleview feature (in this data set, it is the spectral feature);
2) all features: the conventional multifeature concatenation method, which arranges the feature vectors together;
3) PC: implementing the PC transformation on all features concatenation;
4) MNF: executing the minimum noise fraction rotation on all features concatenation; using manifold-learning-based approaches 5) LLE, 6) LTSA, and 7) LE for all features concatenation; and 8) adopting the proposed MFC.

Classification Result

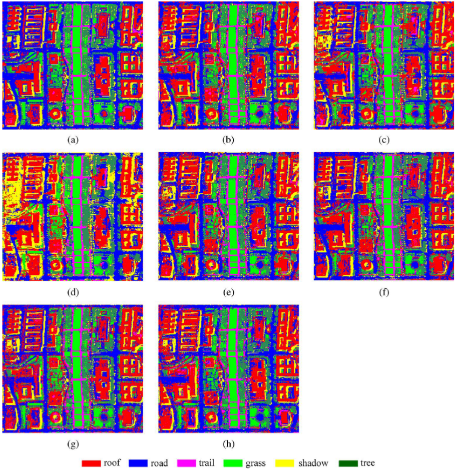


Fig. 5. (a)–(h) Classification maps of the DC data set obtained using features of the following: best feature, all features, PC, MNF, LLE, LTSA, LE, and MFC, respectively.

Classification Result

TABLE II
CLASS-SPECIFIC ACCURACIES IN PERCENTAGE FOR VARIOUS FEATURES

	BF	AF	PC	MNF	LLE	LTSA	LE	MFC
Roof	82.88	83.60	83.83	84.74	89.74	90.16	86.88	91.10
Road	94.16	84.76	91.20	95.19	86.24	91.20	87.57	94.67
Trail	99.75	98.85	99.18	98.77	96.63	97.70	96.55	99.26
Grass	99.08	99.77	98.22	97.99	99.37	98.28	99.60	99.54
Shadow	97.66	98.04	94.95	98.69	97.85	98.79	98.50	98.60
Tree	96.77	95.19	96.59	97.64	97.38	97.55	97.29	97.38
OA	93.15	91.11	92.53	93.29	92.61	93.91	91.72	95.97
Kappa	0.9153	0.8901	0.9077	0.9170	0.9083	0.9244	0.8975	0.9499

Parameter Analysis

1) Effect of Parameter r:

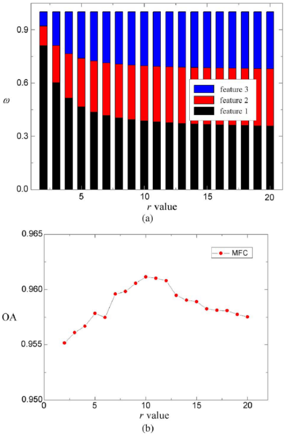


Fig. 6. Relationship of (a) parameter r and weights in each feature and (b) parameter r and OA.

Parameter Analysis

2) Effect of Parameter d:

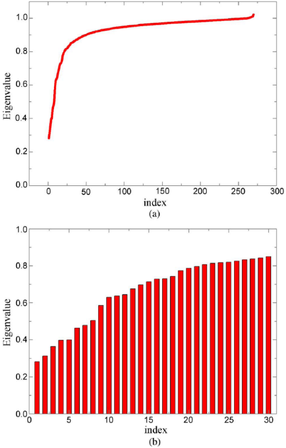


Fig. 7. (a) All eigenvalues and (b) 30 smallest eigenvalues of M in the DC data set, sorted in ascending order.

Parameter Analysis

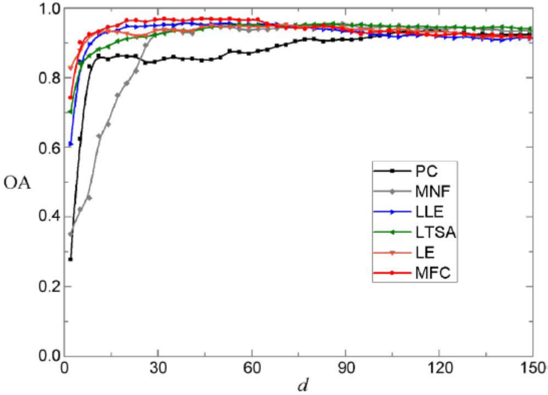


Fig. 8. Relationship of d and OA in the DC data set for six-dimensional reduction approaches.

Classification on the Pavia City Data Set

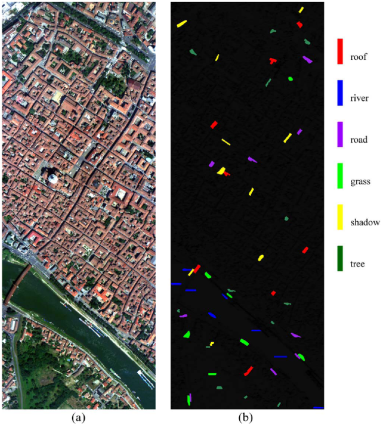
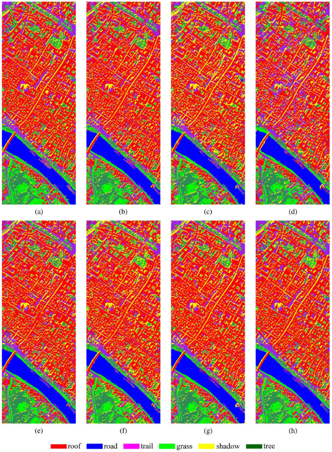


Fig. 11. (a) RGB composite of the Pavia city data set (channels 102, 56, and 31 for RGB) and (b) reference data.

Classification on the Pavia City Data Set



. 12. (a)–(h) Classification maps of the Pavia city data set. (a) Best feature. (b) All features. (c) PC. (d) MNF. (e) LLE. (f) LTSA. (g) LE. (h) MFC.

Classification on the Pavia City Data Set

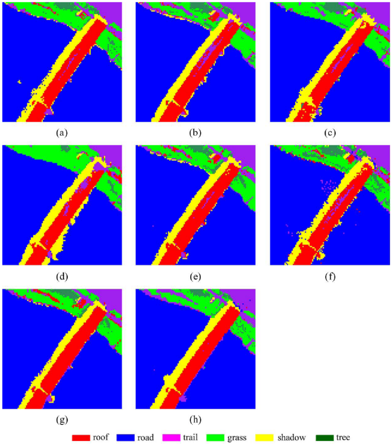


Fig. 13. (a)–(h) Classification maps of a local region at the bridge. (a) Best feature. (b) All features. (c) PC. (d) MNF. (e) LLE. (f) LTSA. (g) LE. (h) MFC.

Classification on the Pavia City Data Set

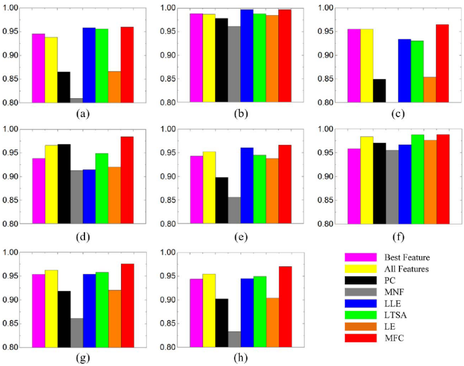


Fig. 14. Classification accuracies of (a)–(f) all classes, (g) OA, and (h) kappa for eight different feature-based classification results.

Classification on the Pavia City Data Set

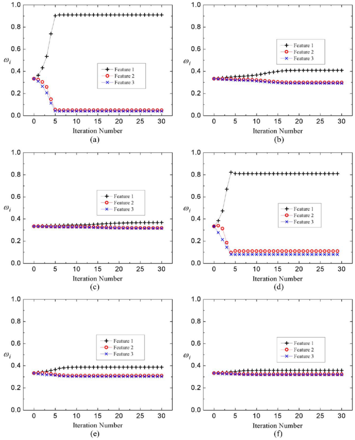


Fig. 15. Alternating optimization converges effectively. (a)–(c) Weights with respect to iteration number using $r = 2$, $r = 10$, and $r = 20$, respectively, for the DC data set. (d)–(f) Weights with respect to iteration number using $r = 2$, $r = 10$, and $r = 20$, respectively, for the Pavia city data set.

Outline

Conclusion

Some of the advantages of our work are as follows.

- First,MFC considers the spectral, texture, and shape features of a pixel to achieve a physically meaningful low-dimensional representation for an effective and accurate classification.
- Second, the weights for each feature are optimized in the objective function of MFC simultaneously without using cross-validation.