High-resolution Hyper-spectral Image Classification with Parts-based Feature and Morphology Profile in Urban Area

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Abstract High-resolution hyper-spectral image (HHR) provides both detailed structural and spectral information for urban study. However, due to the inherent correlation between spectral bands and within-class variability in the data, the data processing of HHR is a challenging work. In this paper, based on spectral mixture analysis theory, a new stack of parts description features were extracted, and then incorporated with a stack of morphology based spatial features. Partially supervised constrained energy minimization (CEM) and unsupervised nonnegative matrix factorization (NMF) were used to extract the part-features. The joint features were then integrated by SVM classifier. The advantages of this method are the representation of physical composition of the urban area by the parts-features and the show of multi-scale structure information by morphology profiles. Experiments with an airborne hyper-spectral data flightline over the Washington DC Mall were performed, and the performance of the proposed algorithm was evaluated in comparison with well-known nonparametric weighted feature extraction (NWFE) and feature selection method. The results shown that the proposed features-joint scheme consistently outperforms the traditional methods, and so can provide an effective option for processing HHR data in urban area.

Keywords parts-features; CEM; NMF; morphology profiles; hyper-spectral image; urban classification

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Introduction

Because of dynamic urban development and high mapping costs, municipal authorities are interested in effective urban surface mapping that can be used for evaluating ecological conditions and also supporting for updates of biotope maps. The most commonly available remote sensing data for urban cover classification are TM/ETM+ and QuikBird, etc. However, the former is not sufficient for accurate classification of structure and shape information, the latter is limited in the information about the spectral nature of the scene. High-resolution hyper-spectral remote sensing data (HHR) from urban areas have recently become available. Such data can provide both detailed struc-
tural and spectral information about urban scenes. When analyzing urban cover with HHR, what we see are those buildings and roads, etc., which have regular shape and structure. There is another fact that the basic physical compositions of urban landscape can be modeled by a universal pattern namely VIS (vegetation-impervious surface-soil) mode\[1\]. Based on these facts, a framework of HHR data processing for urban mapping can be put forward.

When we check for the classification of urban hyperspectral data discussed in recent years\[2\], we find out that the main trend is joining both spectral and spatial information in a classification scheme. For the spatial information, geometry features like shape, size and structure are more important in high spatial resolution images, while texture features are more important in median resolution images\[5\]. Pixel shape index (PSI) was proposed to describe the shape features in the local area by examining the contextual feature along all the directions to some predefined limit around the central pixel, which showed good discrimination between buildings and roads, shadow and elongated water body in high resolution image. Benediktsson\[3,4\] used morphology profile (MP) to explore size information in a multi-scale way, which performed well on many kinds of data (panchromatic, multispectral and hyperspectral data). A Markov random-field-based method using both contextual information and a multi-scale fuzzy line process for classifying high resolution multispectral imagery is investigated in\[7\]. As for spectral feature extraction from high dimension hyperspectral data\[8\] discriminate analysis feature extraction (DAFE) is fast but does not perform well with classes whose mean values are similar, and it produces only $N-1$ reliable features where $N$ is the number of classes. Decision boundary feature extraction (DBFE) does not have these limitations but does not perform well when training sets are small, nonparametric weighted feature extraction (NWFE) takes advantage of DAFE and DBFE. However, the limitation of these methods is that those extracted features are hard to be interpreted. Based on the physical meaning of the unmixed fraction images and the basic physical compositions of urban landscape, Lu et al.\[9\] used fraction images to classify land-use and land-cover (LULC) classes. The fraction images here can be interpreted as parts representation of urban composition.

Suppose that the parts-image is related to the physical material properties, and MPs describes the objects’ structure. Therefore, joining both parts-based features and MPs for urban classification is a reasonable solution. The rest of this paper is organized as follows. In section 1, the spectral unmixing problem is reviewed and parts-features are extracted by non-negative matrix fraction (NMF) and constrained energy minimization (CEM); Section 2 discusses the use of morphology profiles in structure features description. In section 3, we use a support vector classifier to fuse the two types of features. Section 4 details the function of parts-features and the effectiveness of the proposed joining scheme by an airborne HHR data over the Washington DC mall.

## 1 Parts-based spectral feature set

In the past decade, spectral mixture analysis (SMA) has developed as the primary method for extracting multiple urban land covers from a single pixel value, which has been theorized according to Ridd’s V-I-S (vegetation-impervious surface-soil) classification scheme\[1\]. This scheme provides a conceptual model that represents urban environments as a linear combination of three land-cover elements: vegetation, impervious surface and soil. This approach remains problematic, so Small et al.\[10\] developed a more applicable model that establishes substrate, vegetation and dark (SVD) features of the urban environment as components for SMA. Spectral unmixing provides estimates of the percentage of each pixel occupied by each component of the VIS or SVD model.

A reasonable assumption for spectral unmixing is that a spectral measurement of an object results from a linear combination of the spectral signatures of its constituent materials. Hence, in the linear mixing model, a spectral measurement of an object along spectral bands is given by:

$$r = Mf + \epsilon \tag{1}$$

s.t. $f = (f_1, \ldots, f_k)\T$, $\sum_{i=1}^{k} f_i = 1$, $f_i \geq 0$

where $M \geq 0$ is an $m \times k$ matrix whose columns are the spectral reflectance signatures of constituent ma-
terials (endmember). Most of the time knowledge about \( M \) is rare. \( f \) is a vector of fraction abundance, and \( \varepsilon \) is a noise term. For a hyperspectral image data cube, we write it in a block form

\[
Y = MF + E
\]  

(2)

Where \( Y \) is the \( m \times n \) data matrix whose columns are spectral measurements, \( F \) is a \( k \times n \) matrix of fraction abundances, and \( E \) is noise. Then two problems are expected to determine: 1) the type of constituent material and 2) the fraction amount in which these materials appear. It is evident that the unmixing problem is to factorize the measured data matrix into two low rank matrices, which can be used for feature extraction comfortably. With the purpose of feature extraction we expected an unsupervised or partially supervised method. In the following, NMF and CEM are introduced for this problem.

1.1 NMF (nonnegative matrix fraction)

NMF is able to extract underlying features that can be subsequently used for identification and classification. It can be stated in generic form as follows\cite{11}.

Given a nonnegative matrix \( A \in \mathbb{R}^{m \times n} \) and a positive integer \( k < \min(m,n) \), find nonnegative matrices: \( W \in \mathbb{R}^{m \times k} \), \( H \in \mathbb{R}^{k \times n} \) to minimize the functional

\[
f(W,H) = \frac{1}{2} \| A - WH \|_F^2.
\]  

(3)

The product \( WH \) is called a nonnegative matrix factorization of \( A \), although \( A \) is not necessarily equal to the product \( WH \). Clearly the product \( WH \) is an approximate factorization of rank at most \( k \), but the choice of \( k \) is very often problem dependent. Also, the initialization of \( W \) and \( H \) affects the convergence.

Various numerical approaches for the solution of Eq.(3) have been proposed. Generally, they can be divided into three general classes: multiplicative update algorithms, gradient descent algorithms and alternating least squares algorithms. An entire library namely NMFLAB of MATLAB® routines has been created for each class of the NMF algorithms\cite{12}.

Here, we apply NMF to the spectral unmixing problem in an unsupervised manner. Specifically, we minimize the extended cost function Eq.(3) with \( A = Y \) and seek column vectors in basis matrix \( W \) that approximate endmembers in matrix \( M \). We then gather the best computed endmembers into matrix \( B = M \), and solve an inverse problem to compute. The Ridd’s V-I-S and its extension SVD model tell us the basic physical compositions for urban landscape: vegetation, soil, impervious surface, water or dark shade. So 4 or 5 is a better choice for \( k \).

1.2 CEM (constrained energy minimization)

Constrained energy minimization builds on the linear mixture model in Eq.(1). It uses an FIR filter to constrain the desired target signature by a specific gain while minimizing the filter output power. Assume that we are given a finite set of observations \( Y = \{r_1,r_2,\cdots,r_n\} \), where sample pixel vector is \( r_i = (r_{i,1}, r_{i,2}, \cdots, r_{i,m})^T \), \( 1 \leq i \leq n \). Suppose that the desired target signature \( d \) is also known a priori. The objective of CEM is to design an FIR linear filter coefficient \( \omega \) that minimizes the filter output power subject to the following constraint

\[
d^T \omega = \sum_{i=1}^{m} d_i \omega_j = 1
\]  

(4)

Therefore, the average output power produced by the observation set \( Y \) and the FIR filter with coefficient vector \( \omega \) specified by Eq.(4) is given by

\[
\frac{1}{n} \left[ \sum_{i=1}^{n} Y_i^2 \right] = \frac{1}{n} \left[ \sum_{i=1}^{n} (r_i^T \omega)^T \cdot (r_i^T \omega) \right]
\]

\[
= \omega^T \left[ \frac{1}{n} \left[ \sum_{i=1}^{n} r_i r_i^T \right] \right] \omega = \bar{\omega}^T R_{mm} \bar{\omega}
\]  

(5)

where \( R_{mm} \) turns out to be the \( m \times m \) sample autocorrelation matrix of \( Y \). Minimizing Eq.(5) with the filter response constraint \( d^T \omega = \sum_{i=1}^{m} d_i \omega_j = 1 \) yields

\[
\min \left\{ \frac{1}{n} \left[ \sum_{i=1}^{n} Y_i^2 \right] \right\} = \min \{ \omega^T R_{mm} \omega \}
\]

s.t. \( d^T \omega = 1 \)

(6)

The solution to Eq.(6) was shown in Ref.[13] and called the CEM filter with the weight vectors \( \omega^* \) given by

\[
\omega^* = \frac{R_{mm}^{-1} d}{d^T R_{mm}^{-1} d}
\]  

(7)

With this specific constraint CEM can only detect the exact signature with very little flexibility. Therefore, it cannot detect signatures similar to \( d \). As a result, it is not robust to noise. This may create a problem since in many applications acquiring the precise knowledge of \( d \) may not be realistic. More importantly,
even the knowledge of \(d\) can be obtained from real data, it may not be accurate. To remedy this drawback, three approaches\cite{14} are proposed to include all desired similar signatures as multiple constraints, including Multiple Target CEM (MTCEM), Sum CEM (SCEM) and Winner-Take-All CEM (WTACEM).

2 Morphology profile based spatial features

2.1 Mathematical morphology profiles

The applied method for spatial feature analysis is focused on image structural information, and this structural information is collected by applying morphological operators with a multi-scale approach. Granulometries are popular and the powerful tools derived from the mathematical morphology (MM) theory. They are classically used for the analysis of the size distribution of particles in an image, and have recently been introduced in remote sensing image processing for urban areas in multi-scale form. In the following, some basic notion of MM are reviewed, and the morphology profiles (MPs) defined by granulometry are detailed.

The two fundamental operators in mathematical morphology are erosion and dilation. They are applied to an image with a set of known shapes, called the structuring elements (SEs). Opening and closing are a combination of erosion and dilation. The idea behind opening is to dilate an eroded image in order to recover as much as possible the eroded image; in contrast, the idea behind closing is to erode a dilated image in order to recover the initial shape of image structures that have been dilated. It is a common practice to use the opening and closing transforms in order to isolate bright (opening) and dark (closing) structures in images, where bright/dark means brighter/darker than the surrounding features in the images. However, they also modify structures that are still present in the image after the opening/closing. Thus, they can introduce fake objects in the image. To avoid this problem, geodesic morphology and reconstruction should be used\cite{15}. Opening and closing by reconstructions are connected operators that satisfy the following assertion. If the structure of the image cannot contain the SE, then it is totally removed; else, it is totally preserved. For a given SE, geodesic opening or geodesic closing allows one to know the size or shape of some objects presented in the image. The objects that are smaller than the SE are deleted, whereas the others (that are bigger than the SE) are preserved. To determine the shape or size of all elements presented in an image, it is necessary to use a range of different SE sizes. This concept is called granulometry.

MPs are defined by using the granulometry. An MP is composed of the opening profile (OP) and the closing profile (CP). The OP at the pixel \(x\) of the image \(i\) is defined as an \(n\)-dimensional vector:

\[
OP_i(x) = \gamma^{(i)}_v(x), \quad i = 0, 1, \ldots, n \tag{8}
\]

where \(\gamma^{(i)}_v\) is the opening by reconstruction with the \(v\)th disc SE of a size \(s\), and \(n\) is the total number of openings. In addition, the CP at the pixel \(x\) of the image \(I\) is defined as an \(n\)-dimensional vector:

\[
CP_i(x) = \phi^{(i)}_v(x), \quad i = 0, 1, \ldots, n \tag{9}
\]

where \(\phi^{(i)}_v\) is the closing by reconstruction with the same set SEs as above. Noting the closing profile can also be defined as anti-granulometry made with closing by dual reconstruction. Clearly, we have \(CP_v(x) = OP_v(x) = I(x)\). By collating the OP and the CP, the MPs of image \(I\) is defined as \(2n+1\) dimensional vector:

\[
MP(x) = \{CP_0(x), \ldots, CP_n(x), I(x), OP_0(x), \ldots, OP_n(x)\} \tag{10}
\]

After the formulation of MPs, the differential of the morphological profile (DMP) can be defined for each pixel, which is a vector measuring the slope of the opening-closing profile for every step of an increasing SE series. For each pixel, the differential of the opening profile \(DMP_v\) is given by:

\[
DMP_v(x) = OP_v(x) - OP_{v-1}(x), \quad i = 1, \ldots, n \tag{11}
\]

By duality, the differential of the closing profile \(DMP_v\) is given by:

\[
DMP_v(x) = CP_v(x) - CP_{v-1}(x), \quad i = 1, \ldots, n \tag{12}
\]

Generally, the two DMPs are concatenated as a vector:

\[
DMP(x) = \begin{cases} DMP_v(x) & \text{for } i = (n+1), \ldots, 2n \\ DMP_{v+1}(x) & \text{for } i = 1, \ldots, n \end{cases} \tag{13}
\]

The opening operations above only affect structures that are brighter than their immediate neighbors, and closing operations provide information regarding
the structures that are darker than their immediate surroundings. A MATLAB® routine for MPs is given as follows.

**Inputs:** Gray-scale image $X_{osi}$, structure element size array $s[n]$

**Output:** multiscale morphology profile image $m_{p(i_{s+1})_{s|s(c)}}$ (Opening by reconstruction: erosion image of $X$ is used as maker, $X$ is used as mask. Closing by reconstruction is implemented by dual reconstruction).

1. $mp(:,k+1) = \text{reshape}(X,c \times l,1)$;
2. for $j = 1:n$,
3. $se = \text{strel('disk', s[j])}$;
4. $fe = \text{imerode}(X,se)$;
5. $fobr = \text{imreconstruct}(fe, X)$; (construction by opening)
6. $fobrc = \text{imerode}(fobrc,se)$; (construction by closing)
7. $fobrce = \text{imreconstruct}(fobrce, fobrc)$;
8. $mp(:,n+1+j) = \text{reshape}(fobr, c \times l,1)$;
9. $mp(:,n+1-j) = \text{reshape}(fobrce, c \times l,1)$;

eend

2.2 **Interpretation of MP in hyperspectral image**

As stated in the definition of granulometry, when the size of the structuring element reaches the size of one given structure, the structure is removed. This induces a noticeable change of the gray-level values of the corresponding pixel, and as a consequence, a peak in the DMP. Therefore, the position of the greatest value within the DMP is an estimation of the characteristic size of the structure the pixel belongs to. In addition, the position of DMP and its shape also provides a wealth of information to distinguish objects of different sizes. When MP operation was applied to hyperspectral data, a characteristic image needs to be extracted from the data first. Benediktsson$^4$ used principal components of hyperspectral data for this purpose. Considering the variation preserved in the PCs, they suggested to use PCs containing 90% of the total variation, and then the MP operation is applied on these PCs. Finally, a stack vector is built with the MP on each PCs. As a substitution, the parts images generated by spectral mixing analysis which were discussed in section 2 can be used as characteristic images. This is because each parts image corresponds to a physical component of land cover, and the brightness in the image indicates the component’s faction information. As shown in Fig.1, the interesting structures are lighter than the surroundings, which results in an unbalanced DMP (just in the right side). The example of different DMPs presented in Fig.1 tells that classes can be differentiated by profile features; and when parts images are used instead of PCs, the bar graphs are more compact and the estimation of the size is more accurate.
3 Integration of MPs and parts-based features using SVM

3.1 Information fusion

Parts-image is related to the physical material properties, and MP describes the objects’ structure. They represent different kinds of measurements with different distribution type. In order to fuse them together, we concatenate them into a one stacked vector $\{\chi_{mp}, \chi_{p}\}$. $\chi_{mp}$ are MPs, and $\chi_{p}$ are part-based...
features. Then the vector is input to a classifier. In this paper the SVM classifier is used because of its robustness in nonlinear classification and computational efficiency. It is worth noting that the two types of features should be normalized into $[0, 1]$ before the concatenation.

### 3.2 SVM classifier

The SVM classifier\(^{[16,17]}\) of the form $f(x) = w \cdot \Phi(x) + b$ is learned from the data $\{(x_i, y_i)\}_{i=1,2,\cdots,N}$, where $x_i$ is an $n$-dimensional feature vector, $f(x)$ denotes a hyperplane, which separates samples label $y_i = \pm 1$ on each side, and $w$ and $b$ are the parameters of the hyperplane. The hyperplane calculation can be formulated into a constrained optimization problem as follows:

$$
\begin{align*}
\min_{w,b,\xi} & \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \\
\text{s.t.} & \quad y_i(w \cdot \Phi(x_i) + b) \geq 1 - \xi_i, \\
& \quad \xi_i \geq 0, i = 1,\cdots,l
\end{align*}
$$

Its dual is

$$
\begin{align*}
\min_{a} & \quad \frac{1}{2} a^T Q a - e^T a \\
\text{s.t.} & \quad y^T a = 0, \quad 0 \leq a_i \leq C, \quad i = 1,\cdots,l
\end{align*}
$$

where $e$ is the vector of all ones, $C$ is a penalty parameter, $C > 0$ is the upper bound, and $\xi_i$ is slack-variables. $Q$ is an $l$ by $l$ positive semidefinite, $Q_{ij} = y_i y_j K(x_i, x_j)$, and $K(x, x’) = \varphi(x)^T \varphi(x’)$ is the kernel. Here training vectors $x_i$ are mapped into a higher dimensional space by function $\varphi$. Though new kernels are being proposed by researchers, there are four basic kernels: linear, polynomial, radial basis function (RBF) and sigmoid. It is suggested that RBF is a reasonable first choice. The decision function is $\text{sgn} \left( \sum_{i=1}^{l} y_i a_i K(x_i, x) + b \right)$. The SVM optimization problem was solved by using a library named LIBSVM\(^{[18]}\).

The design of SVM for remote sensing application needs to handle several issues. The first is the multiclass problem, while SVMs were originally designed for binary classification. One approach for multiclass SVM is by constructing and combining several binary classifiers. Three multiclass SVMs have been implemented based on solving several binary classifications: one-against-all (OAA), one-against-one (OAO), and directed acyclic graph SVM (DAGSVM)\(^{[17]}\). Experiments indicate that the OAO and DAG methods are more suitable for practical use. In this paper, the DAGSVM is employed. The second problem is model selection. The goal of model selection is to choose the best kernel function and to determine parameters for the kernel. RBF kernel is preferred in this paper. $K(x, x’) = \exp(-\gamma ||x_i - x_j||^2)$, so there are two parameters $(C, \gamma)$ while using the kernel. We employ a “grid-search” on $C$ and $\gamma$ using five-fold cross-validation. In order to accelerate the search procedure, a coarse grid is used first; after identifying a “better” region on the grid, a finer grid search on the region can be conducted. In our experiments, a coarse logarithm grid $[-2:2:12]$ for $C$ and $[-14:1:3]$ for $\gamma$ is first conducted, and then do a finer search in $[(\text{bestlogc}-2):0.5:(\text{bestlogc}+2)]$ for $C$ and $[(\text{bestlogc}-2):0.5:(\text{bestlogc}+2)]$ for $\gamma$. We refer the reader to Refs.\([16,18,19]\)$ for greater detail on SVMs.

### 3.3 Integration scheme with SVM classifier

Based on the theory of spectral unmixing in parts-based feature extraction and morphology profile in objects’ structure measurements discussed in section 2 and 3, a technique route of HHR data processing for urban mapping can be put forward in Fig.2. First a high resolution hyperspectral data with water absorption and low SNR bands removed is used as input. Features for classification include both spectral and structure information. Endmembers for mixing pixel analysis (MPA) are extracted from HHR by automatic methods such as N-FINDR and IEA, etc., or gathered by reference data. Here mixing pixel analysis is implemented by CEM or NMF; Parts-based images are generated from MPA, and then adjusted according to endmembers’ category attribution. Structures information is described by MPs, which are calculated from PCs or parts-image based characteristic images. Because of data redundancy and high correlation, MPs should be simplified before integrating with parts-based features, which is implemented by nonparametric weighted feature extraction (NWFE) technique or Bhattacharyya distance measure based feature selection technique. The two kinds of features are input into a spectral-spatial joined classifier, such as support vector classifier. Finally, we get the classification map.
4 Experiment and validation

To test and validate the parts-based features’ effectiveness and their combination for urban classification, two experiments are conducted. For these experiments we used an airborne hyperspectral data, which can be seen as a high resolution hyperspectral image.

4.1 Data description

Fig.3 shows a simulated color IR view of an airborne hyperspectral data flightline over the Washington DC Mall. The sensor system used in this case measured pixel response in 210 bands in the 0.4 to 2.4 μm regions of the visible and infrared spectrum. Bands in the 0.9 and 1.4 μm region where the atmosphere is opaque have been omitted from the data set, leaving 191 bands. The data set contains 280 scan lines with 307 pixels in each scan line. The area shows the following ground cover types: roofs, streets, path, grass, trees and shadow. The pixels for training and testing of each class are listed in Table 1. In order to test the influence of train samples to classification accuracy, we have randomly selected two different sizes of training samples from the training data in Table 1.

| Data set class | Number of pixels |
|----------------|------------------|
|                | Training set     | Test set   |
| Roof           | 491              | 9506       |
| Road           | 375              | 3828       |
| Path           | 112              | 969        |
| Lawn           | 111              | 2543       |
| Trees          | 240              | 1292       |
| Shadow         | 86               | 493        |
| Total          | 1415             | 18631      |

Washington DC Mall airborne hyperspectral data and image for test land cover classes and associated numbers of pixel for train and test.
4.2 Experiments with Washington DC Mall hyperspectral data

4.2.1 Comparison of CEM, NMF, NWFE and origin spectral bands

The selection of appropriate spectral endmembers is essential to the accuracy of the mixture model. The methodology described here for CEM relies on manual selection of endmember spectra from the apexes of mixing space and reference region of interested areas. In the experiment data, vegetation endmember corresponds to lawn and trees; dark endmember corresponds to shadow; and impervious surface corresponds to roofs, paths and roads. The roofs are composed of two high albedo roofs and two low albedo roofs. Endmembers selected for CEM are shown in Fig.4. NMF is solved by projected gradient method. The rank $k$ is set as 5, and $W$ is initialized by non-negative SVD, then $H$ is initialized with positive least square. NWFE is applied to a 48-band image sampled internally from the 191-band image with the first 7 components containing $>99\%$ eigenvalues accumulation, which is implemented by Multispec© software, where the reduced 48 bands were used for the sake of simplicity calculation. We selected 14 important bands (imp-Spec-bands) for urban cover from the 191 bands data with the purpose of classification comparison. They are \(\{0.438, 0.498, 0.538, 0.580, 0.640, 0.675, 0.740, 0.846, 1.106, 1.290, 1.710, 2.000, 2.180, 2.330\} \mu m\) bands, which was described as the most important bands for urban mapping by Martin Herold\[20\]. The four types of features are classified by SVM. The obtained classification accuracy statistics of test data are listed in Table 2. Two sets of training data S40 and S80 were used. They have been tested 6 times and the mean value and standard deviation are presented. From Table 2, it can be seen that CEM has similar accuracy with NWFE and imp-Spec-bands data. NMF has the highest accuracy. Therefore, CEM and NMF are successfully applied here.

$$\text{Table 2 Classification accuracy statistics of test data for CEM, NMF, NWFE, and origin spectral bands}$$

| Features | Parts-features | CEM | NMF | NWFE | Imp-Spec-bands |
|----------|----------------|-----|-----|------|----------------|
| OA(%)    | S40 \(93.52842 \pm 0.97809\) | 94.2168 ± 0.84499 | 93.64322 ± 2.11033 | 93.37038 ± 1.42989 | 94.06903 ± 0.70986 |
| Kappa    | S40 \(0.90435 \pm 0.01375\) | 0.91512 ± 0.01221 | 0.9065 ± 0.03009 | 0.90243 ± 0.02073 |
|          | S80 \(0.89937 \pm 0.01132\) | 0.92353 ± 0.01233 | 0.90613 ± 0.01177 | 0.91272 ± 0.00999 |

S40: 40 pixels are random selected from train data for each class; S80: 80 pixels are random selected from train data in for each class.

4.2.2 Comparison of the combination of CEM, NMF, NWFE with MPs and DMPs respectively

Structure element type for MP is ‘disk’, and elements in structure size array are from 1 to 13 stepped by 2. The characteristic images are the first two components of the 48 bands image. So finally 30-band MP images and 28-band DMP images are obtained. Because of the data redundancy and high correlation between these bands, 30-band MP and 28-band DMP are preprocessed by feature selection and feature extraction technique in Multispec© software. In Fig.5, we selected the 18 bands subset because it performed good separation between classes and had high Kappa value. The eigenvalue statistic for feature extraction of DMP and MP are shown in Fig.6 and Fig.7. In order to test the effect of the joint between morphology structure features and spectral features, we have made 9 joint types. They are the combination between the dimension reduction result of DMP (DR-DMP, 18 bands) with CEM, NWFE and NMF respectively; NWFE features of DMP (NWFE- DMP) with CEM, NWFE
Fig. 5  Feature selection process of 28 bands DMP max mean distance is measured in every bandset Kappa statistic is also applied in every bandset

Fig. 6  Eigenvalue description for MP NWFE features

Fig. 7  Eigenvalue description for DMP NWFE features

Fig. 8  Classification accuracy of the 9 joint type and three kind MPs features

5  Conclusion

A stack of novel parts-based features were proposed to combine with spatial structure features for urban high resolution hyperspectral image classification with SVM classifier. The successful usage of CEM and NMF in urban classification shows that SMA fraction images are not only able to provide subpixel information but also can represent as physical features for pure pixel classification. In addition, the successful joint evinces a rational method for HHR data classification in urban areas. In our future work, been trained by two set reference data (80, 40) which are randomly selected from the training data in Table 1. Clearly, J-ND has relatively high accuracy although NWFE-DMP individual is low in Fig.8. Parts-based features performed very well, especially CEM was more robust than NWFE and NMF when classified with morphology features. The increase of training data improved classification accuracy. Fig.9 illustrates the classification results using NWFE features of DMP with CEM, NWFE and NMF, and NWFE features of DMP only. The visual comparisons of the four classifications in Fig.9 show varying degrees of accuracy in pixel assignment. The first three classification results have similar results in road and path. Fig.9(a) has more accurate discrimination between lawn and trees, it did a better job in fragmentary area because of its subpixel property. Fig.9(a) and Fig.9(c) performed better in the discrimination between roof and roads. Fig.9(d) misclassified some low albedo imperious into shadow.

and NMF respectively; and NWFE features of MP (NWFE-MP) with CEM, NWFE, and NMF respectively. For simplicity, we note the three types of joints as “J-DD”, “J-ND”, “J-NM”. They are integrated into the SVM classifier. Three morphology features (DR-DMP, NWFE-DMP, and NWFE-MP) are classified by SVM individually. Finally, Kappa statistics are obtained for the 12 feature sets, all of them have
morphological texture features and their joint with parts-based features are expected to be explored for rural area classification.

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