Comparison of Vector Stacking, Multi-SVMs Fuzzy Output, and Multi-SVMs Voting Methods for Multiscale VHR Urban Mapping

Xin Huang and Liangpei Zhang

***Abstract*—The objective of this letter is to integrate multiscale information for urban mapping using very high resolution (VHR) imagery. Three multiscale fusion methods were presented: 1) vector stacking (VS); 2) multiple support vector machines (multi-SVMs) fuzzy output; and 3) multi-SVMs voting. Two kinds of spatial features were used to obtain multiscale representations of VHR images: morphological structural features and object-based approaches. In experiments, the Reflective Optics System Imaging Spectrometer-03 Pavia Center and University, the Hyperspectral Digital Imagery Collection Experiment Washington DC Mall, and the Quickbird Beijing data sets were used for algorithm validation. The experimental results revealed that, in most cases, the VS fusion outperformed other methods because it was able to create a new high-dimensional multiscale feature space and enhance the class separability. It was also shown that the multi-SVMs fuzzy fusion could optimize and reorganize the multiscale information effectively. Furthermore, multi-SVMs fuzzy output was better than multi-SVMs voting because the former was able to exploit the probabilistic output, while the latter only considered the crisp classification label. In addition, it is suggested that VS fusion is suitable for morphological features; however, for the object-based classification, the multiscale fusion methods do not necessarily yield better results than the single-scale classification in terms of accuracies.**

***Index Terms*—Fusion, high resolution, morphological, multiscale, object-based classification, support vector machines (SVMs).**

I. Introduction

IN RECENT years, the processing techniques for very high resolution (VHR) imagery have received much attention since this data type can provide a large amount of detailed ground information. However, its availability poses challenges to image-information extraction and classification due to the complex spectral attributes within each land-cover class and between different classes. It is well known that exploitation of spatial information is an efficient way to address this problem [1]. The scale selection or optimization is a very important technique for spatial feature extraction; however, few multiscale fusion methods have been proposed.

Although recently it has been shown that spatial features can be extracted by performing unsupervised segmentation [2], [3], the multiscale fusion is important for the VHR images in particular. The reasons are summarized as follows.

1) The geostatistical analysis indicated that there was no single-analysis scale that would adequately characterize the range of textural conditions present in VHR images [4].
2) The multiscale methods can mimic human perception in identifying objects.
3) The multiscale methods can exploit the rich spatial information contained in the VHR images; furthermore, it is able to reduce the spectral variation within a homogeneous region and simultaneously preserve detailed structures.

Some multiscale fusion methods have been reported; however, most of them referred to the vector-stacking algorithm. Binaghi *et al.* [5] built a multiscale cognitive pyramid using Gaussian pyramid resampling, and a multilayer perceptron was then used to classify the concatenated multiscale features. Benediktsson *et al.* [6] used the multiscale derivative of the morphological profiles (DMPs) combined with a neural-network classifier for high-resolution urban-image classification. Afterwards, the DMPs were extended to extended morphological profiles (EMPs) by constructing the morphological features based on the first principal components of urban hyperspectral images [7], [8]. Bruzzone and Carlin [9] proposed a multilevel context-based system for VHR image classification based on the fractal net evolution approach (FNEA) segmentation with multiple scale parameters, and the multilevel features were then stacked and classified via support vector machines (SVMs). More recently, Huang and Zhang [10] has compared different multiscale structural features and multilevel object-based approaches using vector stacking (VS) fusion. Their experiments showed that, for the multiscale structural features, EMPs outperformed the gray level cooccurrence matrix (GLCM) textures; on the other hand, for the multilevel object-based features, the mean-shift (MS) analysis was superior to the FNEA.

It is worth noting that most of spatial features are related to scale selection and optimization, such as the analysis windows of GLCM, spatial constraint of Pixel Shape Index (PSI) [11], sizes of structural element for morphological operators, scale parameters of FNEA, and bandwidths of MS analysis. Therefore, it is worthwhile proposing new multiscale fusion algorithms and comparing them with the VS. In this context, this letter proposed two new multiscale fusion methods, namely, multi-SVMs fuzzy output and multi-SVMs voting. In experiments, the multiscale structural features (MPs, DMPs, EMPs) and the multilevel object-based features (FNEA and MS) were

Manuscript received July 3, 2009; revised August 19, 2009. Date of publication October 30, 2009; date of current version April 14, 2010. This work was supported by the National Natural Science Foundation of China under Grants 40771139 and 40930532.

The authors are with the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan 430079, China (e-mail: huang_whu@163.com).

Digital Object Identifier 10.1109/LGRS.2009.2032563

used for evaluation and comparison of the presented multiscale fusion methods.

II. Multiscale Feature Extraction

A. MPs, DMPs, and EMPs

MPs, DMPs, and EMPs are based on some basic morphological operators, such as opening and closing, used to remove small bright (opening) or dark (closing) details while leaving the overall features relatively undisturbed [12]. They are applied to a gray image with a set of a known shape, called structuring element (SE). Morphological operators are usually implemented using reconstruction filter because this family of filters is better for shape preservation than classical morphological filters [12].

Let $\gamma^{\mathrm{SE}}(x)$ and $\phi^{\mathrm{SE}}(x)$ be the morphological opening and closing by reconstruction (CBR) with SE for pixel x. MPs can be expressed using opening-by-reconstruction (OBR) and CBR

$$\mathrm{MPs} = \left\{ \prod_{\mathrm{OBR}}, \prod_{\mathrm{CBR}} \right\} \quad (1)$$

$$\prod_{\mathrm{OBR}}(x) = \left\{ \prod_{\mathrm{OBR}}^{\mathrm{SE}} : \prod_{\mathrm{OBR}}^{\mathrm{SE}}(x) = \gamma^{\mathrm{SE}}(x)\ \forall \mathrm{SE} \in [0, n] \right\} \quad (2)$$

$$\prod_{\mathrm{CBR}}(x) = \left\{ \prod_{\mathrm{CBR}}^{\mathrm{SE}} : \prod_{\mathrm{CBR}}^{\mathrm{SE}}(x) = \phi^{\mathrm{SE}}(x)\ \forall \mathrm{SE} \in [0, n] \right\} \quad (3)$$

where $\mathrm{SE} \in [0, n]$ means structural elements with different radius. DMPs are then defined as vectors where the measures of the slopes of the MPs are stored for every step of an increasing SE series

$$\mathrm{DMPs} = \{\mathrm{DMP}_{\mathrm{OBR}}, \mathrm{DMP}_{\mathrm{CBR}}\} \quad (4)$$

$$\mathrm{DMP}_{\mathrm{OBR}} = \Big\{\mathrm{DMP}_{\mathrm{OBR}}^{\mathrm{SE}}(x) = \left|\Pi_{\mathrm{OBR}}^{\mathrm{SE}}(x) - \Pi_{\mathrm{OBR}}^{\mathrm{SE}-1}(x)\right|, \mathrm{SE} \in [1, n]\Big\} \quad (5)$$

$$\mathrm{DMP}_{\mathrm{CBR}} = \Big\{\mathrm{DMP}_{\mathrm{CBR}}^{\mathrm{SE}}(x) = \left|\Pi_{\mathrm{CBR}}^{\mathrm{SE}}(x) - \Pi_{\mathrm{CBR}}^{\mathrm{SE}-1}(x)\right|, \mathrm{SE} \in [1, n]\Big\}. \quad (6)$$

It should be noted that the (D)MPs are extended to EMPs when the stacked vector is composed of the morphological features constructed on the first several spectral components extracted from hyperspectral data.

B. Multilevel Object-Based Features

1) Multilevel FNEA Algorithm: FNEA is a bottom-up region-merging technique starting from a single pixel [13]. In an iterative way, adjacent objects are merged into new larger segments at each subsequent step. The region-merging decision is defined as the heterogeneity difference between the new object and the constituent objects

$$\Delta H = \sum_{b=1}^{B} W_b[N_{\mathrm{merge}}\delta_{\mathrm{merge}} - (N_{\mathrm{obj1}}\delta_{\mathrm{obj1}} + N_{\mathrm{obj2}}\delta_{\mathrm{obj2}})] \quad (7)$$

where W_b controls the weight of band b $(1 \leq b \leq B)$, N_{merge}, N_{obj1}, and N_{obj2} represent the number of pixels within the merged objects, object 1 and object 2, respectively. δ_{merge}, δ_{obj1}, and δ_{obj2} are the corresponding standard deviations. When a possible merge of a pair of image objects is examined, the merge is performed when the criteria index ΔH is smaller than the scale parameter T (i.e., $\Delta H \leq T$). The segmentation process stops as soon as this condition is not met by any possible merge.

The multilevel object-based representations can be obtained based on the FNEA algorithm with increasing values for scale parameters (T). The multilevel feature vector for pixel x is expressed as

$$f(x) = \left\{ f_l(x), l \in [1, L] : f_l(x) = \left[f_l^b(x)\right]_{b=1}^{B} \right\} \quad (8)$$

where L and B are the number of levels and spectral bands, respectively. $f_l(x)$ represents the average spectral values of the object for pixel x at level l.

2) Multiscale MS Analysis: MS is an efficient feature-space-analysis approach that is capable of delineating arbitrarily shaped clusters due to its nonparametric nature. It is able to exploit contextual homogeneity in a local area and at the same time preserve edge and detailed information. This characteristic has found MS a potential tool for spatial feature extraction from VHR images [14]. The multiscale MS analysis approach was proposed by Huang and Zhang [10]. The processing steps can be briefly summarized as follows:

Step 1) definition of a series of spectral and spatial bandwidths;
Step 2) MS procedure for each couple of bandwidths;
Step 3) object extraction based on the converged results;
Step 4) repeating steps 2 and 3 for multiple bandwidths;
Step 5) multiscale features are calculated based on the objects at different levels. The resulting multiscale vector for pixel x can be also written as formula (8).

The results in [14] revealed that the number of clusters became stable when spatial bandwidth was increased, and the number of clusters was more sensitive to spectral bandwidth than spatial bandwidth. Therefore, in this letter, the spatial bandwidth was assigned as a constant for each image scene, and the value was estimated using the most frequent PSI value [14]. Hence, the multiscale MS analysis was actually implemented with a series of spectral bandwidths.

III. Multiscale Information Fusion

A. VS

The VS fusion can be simply expressed as

$$x \in k \Leftrightarrow k = \mathrm{Cla}\,(f(x)) \quad (9)$$

where $f(x)$ is the multiscale feature vector of pixel x, and $\mathrm{Cla}(f(x))$ denotes the class prediction of a unique classifier with k being the class label. The VS method always increases the dimensionality of feature space significantly; therefore, SVM classifier is often used with the VS fusion considering its insensitivity to the dimensionality of features [9], [10].

B. Multi-SVMs Fuzzy Output

The multi-SVMs fuzzy fusion exploits the probabilistic output of multiclass SVMs based on the pairwise classification strategy [15]. The probability values for pixel x with scale l can be written as

$$f_l(x) = \left\{ f_l^1(x), f_l^2(x), \ldots, f_l^k(x), \ldots, f_l^K(x) \right\} \quad (10)$$

where k ($k \in \{1, 2, \ldots, K\}$) is a class label. In the case of single scale (for instance, at scale l), the multiclass SVM decision rule is

$$x(l) \in \arg\max_{k} \left(f_l^k(x)\right) \tag{11}$$

where $f_l^k(x)$ is the probability estimate for class k of scale l and falls in the range of zero–one. Therefore, we can construct a fuzzy set for each scale based on the multiclass SVM probability values and then the optimal scale is determined by comparing the uncertainties of different fuzzy sets. The computation steps are the following:

Step 1) computation of the multiclass output for each scale;

Step 2) normalization of the probability values for each scale

$$\hat{f}_l^k(x) = \frac{f_l^k(x) - \min\limits_{k,x}\left(f_l^k(x)\right)}{\max\limits_{k,x}\left(f_l^k(x)\right) - \min\limits_{k,x}\left(f_l^k(x)\right)}. \tag{12}$$

Step 3) calculation of the fuzziness degree for the probability values of each scale using α-quadratic entropy function [16] (according to the suggestion in [16], $\alpha = 0.5$), therefore

$$H_{\alpha\mathrm{QE}}(l) = \frac{1}{n2^{-2\alpha}} \sum_{k=1}^{K} \left(\hat{f}_l^k(x)\right)^{\alpha} \left(1 - \hat{f}_l^k(x)\right)^{\alpha}. \tag{13}$$

Based on (13), the uncertainty for the SVM of scale l can be defined as

$$w(l) = 1 - \frac{H_{\alpha\mathrm{QE}}(l)}{\sum\limits_{l=1}^{L} H_{\alpha\mathrm{QE}}(l)}. \tag{14}$$

It should be noted that larger $w(l)$ means more reliable decision [16]. Therefore, the multiclass SVM can be extended to the multiscale version

$$x \in \arg\max_{l,k} \left(w(l) \cdot \hat{f}_l^k(x)\right) \tag{15}$$

where $w(l)$ is negatively related to the uncertainty of the decision result of scale l; therefore, it is used as the weight of the probability value to favor the scale that is more reliable. Equation (15) can be viewed as a multiscale extension of multiclass SVM in (11).

C. Multi-SVMs Voting

The multi-SVMs voting algorithm selects the class label by comparing the results of all the L single-scale SVMs. The voting steps are described as follows:where $\mathrm{Vote}_k(x)$ is the number of votes for class k. The final label of pixel x is determined as

$$x \in \arg\max_{k} \left(\mathrm{Vote}_k(x)\right). \tag{16}$$

for $1 \le l \le L$, and $1 \le k \le K$
  if $x(l) \in k$ (i.e., $\arg\max\limits_{k}(f_l^k(x)) = k$)
    $\mathrm{Vote}_k(x) = \mathrm{Vote}_k(x) + 1$; // $\mathrm{Vote}_k(x) = 0$ for initialization
  endif
endfor

TABLE I
INFORMATION CLASSES OF THE FOUR DATA SETS

Datasets		Information Classes
ROSIS	Centre	Water, Trees, Asphalt, Bricks, Bitumen, Tiles, Shadow, Meadows, Bare Soil
	University	Trees, Asphalt, Bitumen, Gravel, Metal Sheets, Shadow, Bricks, Meadows, Bare Soil
HYDICE	DC, Mall	Roads, Grass, Trees, Trail, Shadow, Water, Roofs
Quickbird	Beijing	Grass, Trees, Lake, Pool, Trails, Bank, Shadow, Highway, Roofs

TABLE II
FOUR-SCALE PARAMETERS FOR DIFFERENT FEATURES

Datasets	Multiscale Parameters for Different Features			
	(D)EMPs, MPs (Radius of SE)	FNEA (T)	MS	
			h_{spatial}	h_{spectral}
ROSIS, Center	3, 5, 7, 9	0, 10, 20, 30	8	0, 5, 10, 15
ROSIS, University	3, 5, 7, 9	0, 10, 20, 30	8	0, 10, 20, 25
DYDICE, DC	3, 5, 7, 9	0, 10, 20, 30	5	0, 10, 20, 30
Quickbird, Beijing	3, 5, 7, 9	0, 10, 20, 30	8	0, 6, 8, 10

IV. EXPERIMENTS AND ANALYSIS

Four VHR data sets are used for validation of the multiscale algorithms, and the classes are listed in Table I.

1) Pavia Centre and University data sets. The Pavia data sets used in this study were collected in the framework of the HySens project, managed by the German Aerospace Center (DLR) and sponsored by the European Union. The images were acquired by the optical sensor Reflective Optics System Imaging Spectrometer (ROSIS) during a flight campaign over Pavia, northern Italy, on July 8, 2002 from 10:30 A.M. to 12:00 noon. Hyperspectral channels (102 for Center and 103 for University) were collected in the 0.43–0.86-μm region of the visible and infrared spectrum with 1.3-m spatial resolution. The training/test samples were the same as with previously published literature [17].
2) Hyperspectral Digital Imagery Collection Experiment (HYDICE) DC Mall data set. A total of 210 bands were collected in the 0.4–2.4-μm region of the visible and infrared spectrum. The water-absorption bands were then deleted, resulting in 192 channels. In experiments, the hyperspectral features were extracted using the nonnegative-matrix-factorization transformation [10], [14], in order to avoid hyperdimensional scale space and reduce computational cost.
3) Pan-sharpened Quickbird images in Beijing, with RGB bands and spatial resolution of 0.61 m.

A. Comparison of the Three Fusion Methods

In this experiment, four-scale spatial features were used for information fusion. The parameters were listed in Table II.

In the experiments, the SVM classifiers were implemented using Gaussian radial-basis function (RBF) kernels. The penalty parameter C was fixed to 500, and the parameter of the RBF kernel was set to the inverse of the dimension of the input feature. Classification accuracies of single-scale and multiscale were compared in Tables III–VI for the four data sets, respectively. It should be noted that "scale 1" for FNEA and MS represents the pixelwise classification. By observing the statistics, it can be found that the VS fusion gave the highest

TABLE III
CLASSIFICATION ACCURACIES (PERCENT) OF MULTISCALE FUSION (PAVIA CENTRE)

		EMPs	MPs	FNEA	MS
Single Scale	S1	97.4	97.2	95.7	95.7
	S2	97.2	97.8	96.6	97.3
	S3	96.8	98.0	94.9	95.4
	S4	97.4	97.7	95.5	97.0
Multiscale Fusion	VS	**98.4**	**98.4**	**97.7**	**98.1**
	Fuzzy	**98.0**	**98.2**	**97.1**	**97.5**
	Vote	**97.8**	**98.0**	**97.0**	**97.8**

TABLE IV
CLASSIFICATION ACCURACIES (PERCENT) OF MULTISCALE FUSION (PAVIA UNIVERSITY)

		EMPs	MPs	FNEA	MS
Single Scale	S1	80.1	80.6	71.3	71.3
	S2	77.6	79.4	73.6	71.2
	S3	79.9	76.9	70.4	83.2
	S4	84.3	83.0	77.4	80.5
Multiscale Fusion	VS	**89.3**	**86.8**	**78.4**	**83.4**
	Fuzzy	83.5	82.2	**78.0**	80.8
	Vote	**84.3**	82.3	74.2	80.8

TABLE V
CLASSIFICATION ACCURACIES (PERCENT) OF MULTISCALE FUSION (HYDICE DC)

		EMPs	MPs	FNEA	MS
Single Scale	S1	94.6	94.9	85.8	85.8
	S2	88.4	96.3	93.9	86.8
	S3	92.8	96.8	94.3	97.1
	S4	90.5	97.2	92.4	93.0
Multiscale Fusion	VS	**94.9**	**98.8**	93.7	87.9
	Fuzzy	**95.1**	**97.5**	93.4	92.9
	Vote	**95.2**	**97.2**	92.9	90.9

TABLE VI
CLASSIFICATION ACCURACIES (PERCENT) OF MULTISCALE FUSION (QUICKBIRD)

		DMPs	MPs	FNEA	MS
Single Scale	S1	83.3	83.7	77.4	77.4
	S2	85.1	86.2	80.2	80.9
	S3	84.9	87.3	86.3	78.1
	S4	89.3	89.4	82.4	87.7
Multiscale Fusion	VS	**92.6**	**91.2**	85.1	83.7
	Fuzzy	**89.9**	87.6	81.0	82.2
	Vote	88.2	86.0	81.6	79.9

accuracies for all the features in most cases. On the other hand, the multi-SVMs fuzzy output was slightly better than multi-SVMs voting in terms of the fusion accuracies. The fuzzy and voting algorithms can be viewed as efficient since they can achieve comparable results to the optimal accuracy of the single-scale classification.

The satisfactory performance of VS can be attributed to the fact that it is able to create a new and hyperdimensional scale space. The new feature space has more potential to discriminate some classes which may be not separable in the pixel level or the single-scale space. On the other hand, the multi-SVMs fuzzy fusion is a scale selection and optimization method. It chooses the optimal scale for each pixel in the image by evaluating the uncertainties of single-scale SVM. Its accuracies were slightly lower than VS because it was not able to yield a new feature space and did not enhance the class separability. However, the fuzzy fusion was superior to the voting approach due to the fact that the former exploited the probability values, but the latter only considered the crisp output.

TABLE VII
PARAMETERS FOR DIFFERENT DIMENSION OF SCALE-SPACE (UNIVERSITY DATASET)

Dataset	Scale Dimension	Multiscale Parameters of Different Features: DMPs, MPs (Radius of SE)	FNEA (T)	MS (h_{spectral})
ROSIS University	Dual	3, 9	10, 30	20, 25
	Four	3, 5, 7, 9	0,10,20,30	0, 10, 20, 25
	Multiple	3, 5, 7, 9, 11, 13	0, 5, 10, 15, 20, 25, 30, 35	0, 5, 10, 15, 20, 25, 30

TABLE VIII
CLASSIFICATION ACCURACIES (PERCENT) FOR THE SCALE-SPACE DIMENSIONALITY ANALYSIS (UNIVERSITY DATASET)

Features	Dimension	Highest Accuracy of Single-Scale	Multiscale Fusion: Vector Stacking (VS)	Multi-SVMs Fuzzy Output	Multi-SVMs Voting
DMPs	Dual	84.3	**85.5**	**85.2**	82.0
	Four	84.3	**89.3**	83.5	**84.3**
	Multiple	84.9	**91.1**	**85.2**	**85.7**
MPs	Dual	83.0	**85.3**	**84.1**	**85.0**
	Four	83.0	**86.8**	82.2	82.3
	Multiple	84.1	**85.4**	80.3	**84.2**
FNEA	Dual	77.4	**78.4**	76.2	75.6
	Four	77.4	**78.4**	**78.0**	74.2
	Multiple	77.4	**78.1**	75.9	72.5
MS	Dual	83.2	**87.6**	**85.2**	79.7
	Four	83.2	**83.4**	80.8	80.8
	Multiple	83.2	**88.3**	81.4	81.2

B. Analysis for Dimensionality of Scale Space

The performance of multiscale fusion is related to the scale parameters and the dimensionality of scale space. The objective of this experiment is to study the effects of scale-space dimensionality for different fusion algorithms. To this end, the spatial features were calculated with dual, four, and multiple scales. The parameters were listed in Table VII, and the accuracies were compared in Table VIII. In the table, the multiscale fusion accuracies higher than the optimal accuracy of single-scale classification were highlighted. Based on Table VIII, we can obtain the following observations.

1) In the University data set, the VS fusion outperformed other algorithms for all the features with dual, four, and multiple scales.
2) Scale space with higher dimension did not necessarily lead to better results. This is particularly true for the multi-SVMs output fusion. The explanation is that the fuzzy fusion is based on the measures of fuzziness and uncertainty; therefore, when more scales are considered, the uncertainties and decision errors may be accumulated. This conclusion suggests that the multi-SVMs fuzzy fusion is suitable for multiscale fusion with low dimensions (for instance dual-scale fusion).

C. General Evaluation

In order to generally evaluate the three multiscale fusion methods, the "Z-test" [18] was used to assess the statistical

TABLE IX
STATISTICAL SIGNIFICANCE FOR THE MULTISCALE FUSION ALGORITHMS BASED ON THE FOUR VHR DATA SETS. "OS" REPRESENTS THE OPTIMAL CLASSIFICATION WITH SINGLE SCALE. THE NUMBERS IN THE TABLE INDICATE THE NUMBER OF TIMES THAT THE Z VALUES FALL IN THE CORRESPONDING RANGES.

Z Values		VS/OS	Fuzzy/OS	Vote/OS	Fuzzy/Vote
Z > 1.96		12	8	4	10
|Z| < 1.96	0 < Z < 1.96	0	0	1	2
	-1.96 < Z < 0	0	0	2	1
Z < -1.96		4	8	9	3

significance of different maps. The difference of classification accuracies between features 1 and 2 is said to be statistically significant if $|Z| > 1.96$. Positive Z values indicate that feature 1 is more effective than feature 2, or *vice versa*. The statistical significance was calculated based on the four-scale experiments, and the results were shown in Table IX.

The statistics in the table confirmed the following conclusions: 1) VS fusion gave more significant results compared with the single-scale classification in most cases; 2) the SVM fuzzy fusion was also effective in selecting suitable analysis scale for each pixel; and 3) the fuzzy fusion was significantly superior to the Multi-SVMs voting.

V. CONCLUSION

The main novelty of this study consists in proposing two SVMs-based multiscale fusion methods (multi-SVMs fuzzy fusion and multi-SVMs voting) and comparing their performance with the well-known VS approach. In the multi-SVMs fuzzy output, each SVM is related to a single-scale classification and is weighted by a coefficient measuring uncertainty of the classifier, and the optimal scale is decided by the classifier with both largest output and smallest uncertainty. On the other hand, the multi-SVMs voting chooses the class by majority voting in all the single-scale SVMs.

The proposed two algorithms were validated and compared with the VS based on four VHR urban data sets from three different sensors. Experimental results revealed that the VS algorithm provided the most accurate results because it was able to create a new multiscale feature space and improve the class separability. The proposed multi-SVMs fuzzy output algorithm was also efficient since it was able to give comparable accuracies to the highest accuracies achieved by the single-scale classification. The fuzzy fusion outperformed the voting fusion because the former exploited more discriminant information, while the latter only considered the crisp classification label.

In this experiment, we analyzed the effects of different scale-space dimensions, and the results revealed that the fuzzy algorithm was more suitable for information fusion with low-dimensional scale space due to the accumulation of uncertainties.

The experiments in Table IX showed that in most cases, the VS approach obtained better results. This phenomenon suggests that it is more important to enhance the class separability using the rich spatial and multiscale information contained in the VHR images. On the other hand, it can be found that there are four cases with Z values smaller than -1.96 between the VS fusion and the optimal single-scale classification; furthermore, it is interesting to see that all the four cases correspond to the multilevel object-based features (FNEA and MS algorithms for HYDICE and Quickbird experiments). Therefore, it is found that VS fusion is suitable for morphological features; however, for the object-based classification, the multiscale fusion methods do not necessarily yield better results than the single-scale classification.

ACKNOWLEDGMENT

Dr. X. Huang would like to thank Prof. P. Gamba and Prof. F. Dell'Acqua, University of Pavia, for kindly providing the ROSIS data sets and the ground reference data.

REFERENCES

[1] F. Dell'Acqua, P. Gamba, A. Ferari, J. A. Palmason, J. A. Benediktsson, and K. Arnason, "Exploiting spectral and spatial information in hyperspectral urban data with high resolution," *IEEE Geosci. Remote Sens. Lett.*, vol. 1, no. 4, pp. 322–326, Oct. 2004.

[2] Y. Tarabalka, J. Chanussot, J. A. Benediktsson, J. Angulo, and M. Fauvel, "Segmentation and classification of hyperspectral data using watershed," in *Proc. IGARSS*, Boston, MA, 2008, pp. III-652–III-655.

[3] Y. Tarabalka, J. A. Benediktsson, and J. Chanussot, "Spectral-spatial classification of hyperspectral imagery based on partitional clustering techniques," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 8, pp. 2973–2987, Aug. 2009.

[4] C. A. Coburn and A. C. B. Roberts, "A multiscale texture analysis procedure for improved forest stand classification," *Int. J. Remote Sens.*, vol. 25, no. 20, pp. 4287–4308, Oct. 2004.

[5] E. Binaghi, I. Gallo, and M. Pepe, "A cognitive pyramid for contextual classification of remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 12, pp. 2906–2922, Dec. 2003.

[6] J. A. Benediktsson, M. Pesaresi, and K. Arnason, "Classification and feature extraction for remote sensing images from urban areas based on morphological transformations," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 9, pp. 1940–1949, Sep. 2003.

[7] J. A. Benediktsson, J. A. Palmason, and J. Sveinsson, "Classification of hyperspectral data from urban areas based on extended morphological profiles," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 3, pp. 480–491, Mar. 2005.

[8] M. Fauvel, J. Chanussot, and J. A. Benediktsson, "Kernel principal component analysis for the classification of hyperspectral remote-sensing data over urban areas," *EURASIP J. Adv. Signal Process.*, vol. 2009, pp. 1–14, 2009, DOI: 10.1155/2009/783194.

[9] L. Bruzzone and L. Carlin, "A multilevel context-based system for classification of very high spatial resolution images," *IEEE Trans. Geosci. Remote Sens.*, vol. 44, no. 9, pp. 2587–2600, Sep. 2006.

[10] X. Huang and L. Zhang, "A comparative study of spatial approaches for urban mapping using hyperspectral ROSIS images over Pavia City, northern of Italy," *Int. J. Remote Sens.*, vol. 30, no. 12, pp. 3205–3221, Jun. 2009.

[11] X. Huang, L. Zhang, and P. Li, "Classification and extraction of spatial features in urban areas using high resolution multispectral imagery," *IEEE Geosci. Remote Sens. Lett.*, vol. 4, no. 2, pp. 260–264, Apr. 2007.

[12] P. Soille, *Morphological Image Analysis,* 2nd ed. New York: Springer-Verlag, 2003.

[13] U. C. Benz, P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen, "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information," *ISPRS J. Photogramm. Remote Sens.*, vol. 58, no. 3/4, pp. 239–258, Jan. 2004.

[14] X. Huang and L. Zhang, "An adaptive mean-shift analysis approach for object extraction and classification from urban hyperspectral imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 12, pp. 4173–4185, Dec. 2008.

[15] T. F. Wu, C. J. Lin, and R. C. Weng, "Probability estimates for multi-class classification by pairwise coupling," *J. Mach. Learn. Res.*, vol. 5, pp. 975–1005, Aug. 2004.

[16] M. Fauvel, J. Chanussot, and J. A. Benediktsson, "Decision fusion for the classification of urban remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 44, no. 10, pp. 2828–2838, Oct. 2006.

[17] M. Fauvel, J. A. Benediktsson, J. Chanussot, and J. R. Sveinsson, "Spectral and spatial classification of hyperspectral data using SVMs and morphological profiles," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 11, pp. 3804–3814, Nov. 2008.

[18] G. M. Foody, "Thematic map comparison: Evaluating the statistical significance of differences in classification accuracy," *Photogramm. Eng. Remote Sens.*, vol. 70, no. 5, pp. 627–633, May 2004.