Support Vector Machine and Spectral Angle Mapper Classifications of High Resolution Hyper Spectral Aerial Image

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Abstract : This paper presents two different types of supervised classifiers such as support vector machine (SVM) and spectral angle mapper (SAM). The Compact Airborne Spectrographic Imager (CASI) high resolution aerial image was classified with the above two classifier. The image was classified into eight land use /land cover classes. Accuracy assessment and Kappa statistics were estimated for SVM and SAM separately. The overall classification accuracy and Kappa statistics value of the SAM were 69.0% and 0.62 respectively, which were higher than those of SVM (62.5%, 0.54).

Key Words : supervised classification, support vector machine classifier, spectral angle mapper classifier, high resolution aerial image.

1. Introduction

Image classification is one of the techniques in the domain of satellite image interpretation. Classification of satellite data is the process that operator instructs the computer to perform an interpretation according to certain condition (Janssen, 2000). Multispectral classification is one of the most often used methods of information extraction. This procedure assumes that imagery of a specific geographic area is collected in multiple regions of the electromagnetic spectrum and that the images are in good geometric registration (Jensen, 1996). Traditional classification gives poor result on image classification task, because of the high dimensionality of the feature space (Oliver et al., 1999). Support vector machine (SVM) and Spectral angle mapper (SAM) classification approaches are considered a good candidate for multispectral images (Oliver et al., 1999 and Choen, 1996).

SVM classifier shows good result because of its high generalization performance without the need to add a priori knowledge, even when dimension of input scale is very high (Oliver et al., 1999). On the other hand, the SAM method allows single-step matching of pixel spectra to reference spectra in n-dimensional spectral space (Choen, 1996).

There are number of similar studies that presented the performance and the accuracy of both classifiers

in different ways. For instance, Xiaomei *et al.*, (2009) evaluated the response of both classifiers to noises and uncertainty in original hyperspectral image. Liu *et al.*, (2006) presented the newly proposed novel SVM algorithm and showed that the proposed new algorithm performed with higher accuracy than SAM method. However, there is no research on to test the classification performance in high resolution hyperspectral aerial image. That could be the uniqueness of this research.

In the present study, the SVM and SAM classification approaches were tested to understand their classification performance on high resolution hyperspectral aerial image of the Little Miami River in southwestern Ohio, USA.

2. Materials and methods

1) Study area

The Little Miami River in southwestern Ohio, USA has a drainage area of 4559.36 km2 and stretches in a southwesterly direction for 169.78 km from its origin near South Charleston, Ohio to its confluence with the Ohio River east of Cincinnati, Ohio. It is one of the oldest river groups in the state, having become Ohio's first State and National Scenic River (Fig.1). Geographically it is situated between 39° 26′ N and 84° 07′ W.

2) Data Products

The Hyperspectral remote sensing image having 4 m spatial resolution in 19 spectral bands (Table 1) collected over Little Miamy River watershed (2826 km2) on July and August, 2003 using Compact Airborne Spectrographic Imager (CASI) was used to carry out the land cover classification (NCEA, 2006).
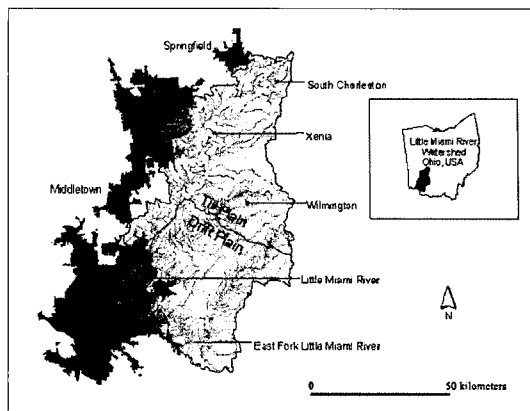

Fig. 1. Orientation Map of the Little Miami River Watershed in Southwestern Ohio, USA.

Table 1. Spectral bands and their properties of CASI data in the Little Miami River

Band	Spectral Region	Band Center (Nm)	Band Width (+/- Nm)	Band Range Nm
1	Blue	449.6	15.0	30.0
2	Blue	490.4	15.0	30.0
3	Green	520.2	9.5	19.0
4	Green	550.2	9.5	19.0
5	Green	574.6	7.7	15.4
6	Green-Red	600	8.6	17.2
7	Red	619.8	7.7	15.4
8	Red	659.6	7.7	15.4
9	Red	674.8	7.8	15.6
10	Red	691	4.9	9.8
11	Red-edge	700.5	4.9	9.8
12	Red-edge	719.6	6.8	13.6
13	Red-NIR	750.1	10.7	21.4
14	NIR	799.9	10.7	21.4
15	NIR	820.1	9.7	19.4
16	NIR Shoulder	845.1	9.8	19.6
17	NIR Peak1	899.9	10.7	21.4
18	NIR Peak2	920.2	9.8	19.6
19	NIR-Moisture Sensitive	937.5	7.9	15.8

3) Classification methods

In this study, the classification was carried out on two flight lines (flight line no. 11 and 12) (Figure 2). The image was classified into 8 classes such as water, forest, corn, soybean, wheat, rural barren, urban built
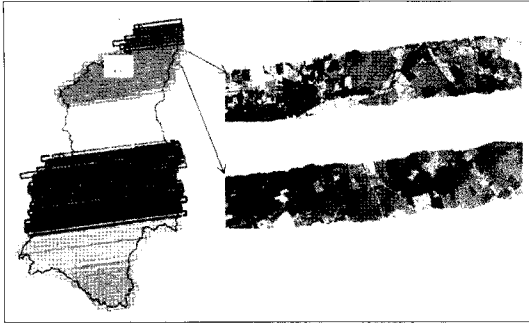
Fig. 2. Flight line 11 and 12 of Little Miami River watershed image used in classification a) Flight line 11, b) Flight line 12.

Table 2. Land use image classes and description

Color	Class name	Description
■	Water	Open water such as lakes, reservoirs, potholes, and stock ponds.
■	Forest	Contains either or both deciduous and coniferous trees in any degree of mixture
■	Corn	Area under cultivation of food and fiber, where corn is the primary crop
▨	Soybean	Area under cultivation of food and fiber, where soybean is the primary crop.
■	Wheat	Area under cultivation of food and fiber, where wheat is the primary crop.
■	Rural barren	Composed of bare soil, rock, sand, silt, gravel, or other earthen material with little (less than 25%) or no vegetation in rural areas
▨	Urban built	Areas covered by structures and impervious surfaces in urban, suburban, and rural areas. Buildings, parking lots, and paved roads typically fall into this class
■	Dry herbaceous	This class mainly includes naturally occurring and unmanaged herbaceous vegetation, and dried out, unhealthy, or stressed croplands.

and dry herbaceous. Each class has a specific color. Table 2 shows land use classes and their description. Support vector machine and spectral angle mapper classification methods were followed. ENVI v4.5 software was used to carry out the two classifications methods.

3. Support vector machine (SVM)

Support vector machine gives good classification result and it is very useful technique for image classification (Hsu et al., 2007). In this section we give a very brief introduction to SVM's.

Let $(x_i, y_i)_{1 \leq i \leq n}$ set of training examples, each example $x_i \in R^n$, n being the dimension of the input space, belongs to a class labeled by $y_i \in \{-1, 1\}$. Our aim is to find a hyperplane which divides the set of example such that all the points with same label are on the same side of the hyperplane (Chapelle, 1999). The hyperplane separating two classes can be defined as:

$$H: \bar{\omega} \cdot \bar{x} - b = 0 \qquad (1)$$

where $\bar{\omega}$ is normal vector of the hyperplane H, $\bar{x}$ is an input vector. Support vectors are the vectors that are close to the boundary of two classes. The support vectors of each class define additional hyperplane H_1 and H_2 (eq 2) that are parallel to separating hyperplane H.

$$H_1: \bar{\omega} \cdot \bar{x} - b = +1$$
$$H_2: \bar{\omega} \cdot \bar{x} - b = -1 \qquad (2)$$

The hyperplane decision function can be written as:

$$sng(\bar{\omega} \cdot \bar{x} - b) \qquad (3)$$

To find the hyperplane H that is in maximum distance from hyperplanes H_1 and H_2 containing support vectors Lagrange's multipliers method is used and object can be amounted to the minimization of the following function:

$$F(\omega, b, \alpha) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \propto_i \propto_j y_i y_j \bar{x}_i \bar{x}_j - \sum_{i=1}^{n} \propto_i \qquad (4)$$

where $0 \leq \alpha_i \leq C$ $\forall$i and $\sum_{i=1}^{n} \alpha_i y_i = 0$ (5)

The complete classification of two sets of vectors is not possible. That is why C parameter is used for presenting penalty in the situation when points are situated between hyperplanes H$_1$ and H$_2$. This parameter is chosen by the user, a larger C corresponding to assigning a higher penalty to errors (Chapelle, 1999). The bigger value of C causes the better fitting of hyperplane to the training set (Urszula, 2005).

In case of non-linear separating, vectors are transformed to higher dimension space using a transformationϕ(x), where the vectors can be linearly separated. In this case function F (eq 4) formed as the follow:

$$F(\omega, b, \alpha) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \phi(\overline{x}_i) \phi(\overline{x}_j)$$

$$\sum_{i=1}^{n} \alpha_i \qquad (6)$$

Knowing that the dot product in this equation can be substituted by kernel function K(x$_i$, x$_j$) the function F (eq 6) can have following form:

$$F(\omega, b, \alpha) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(\overline{x}_i \overline{x}_j) -$$

$$\sum_{i=1}^{n} \alpha_i \qquad (7)$$

The ENVI SVM classifier provides four types of kernels: linear, polynomial, radial basis function (RBF), and sigmoid. The default is the radial basis function kernel, which works well in most cases. The mathematical representation of radial basis function is presented below.

$$K(x_i, x_j) = \exp(-\gamma \|x_i, x_j\|^2), \gamma > 0 \qquad (8)$$

SVM is based on the statistical learning theory (ENVI, 2005) and it is time-consuming with the high resolution images.

ENVI's SVM classification performs hierarchical classification process reducing image resolution. Reduced-resolution improves classification

Table 3. Classification parameters for SVM classifier

Parameter name	Values
Spatial subset	Full Scene
Spectral Subset	18 bands
Kernel Type	Radial basis function
Gamma in Kernel Function	0.056
Penalty parameter	100.000
Pyramid Level	0
Probability threshold	0.00

performance and it does not affect classification result significantly (ENVI, 2005). The hierarchical classification procedures are as follows:

- Resampling the images into low resolution level
- Resampling the region of interest (ROI) to same resolution level
- SVM classifier trains low resolution image and ROI. In the training step, SMV trains each level of resolution, because training for each resolution level gives more accuracy.
- Checking image values that exceed reclassification probability threshold.
- In the next step, SVM examines the next higher resolution pyramid level, but excluding pixels that are marked as classified in the previous lower resolution level.
- Above steps iterates until the highest resolution level of image.

4. Spectral angle mapper (SAM)

SAM permits rapid mapping of the spectral similarity of image spectra to target spectra (Kruse, 1999). This classification method uses n-dimensional angle and computes a spectral angle between each pixel spectrum and each reference (target) spectrum. The smaller spectral means that pixel and target spectra are more similar (Shippert, 2003). Comparing spectral angle between these two spectra is not sensitive in illumination because changing illumination does not change the direction of the vector (ENVI, 2005). The pixels that have angle more
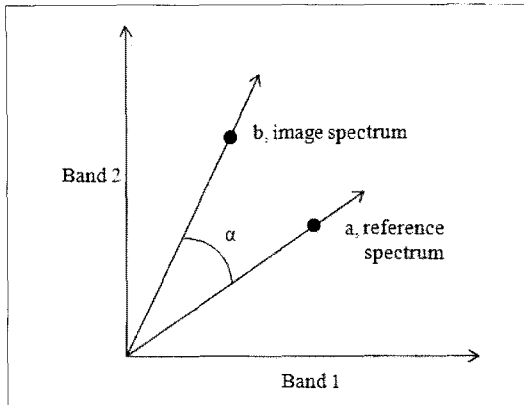
Fig. 3. Vector presentation of a reference and image spectrum for a two band image.

Table 4. Classification parameters for SAM classifier

Parameter name	Values
Spatial subset	Full Scene
Spectral Subset	18 bands
Maximum angle (radians)	Single value (0.100)

than specified threshold in radians are not classified (ENVI, 2005). A simplified representation to explain how the angle between a reference and an image spectrum from two-band data represented on a two-dimensional plot as two points obtained from image data (Park, 2007). The lines connecting each spectrum points (a, b) and the origin contain all possible positions for the sample, corresponding possibly intensity changes due to the illumination variability (Figure 3). The spectral angle (α) between two vectors is independent of their lengths (Park, 2007). This spectral between these two vectors, can be calculated by the following equation (9).

$$\alpha = \cos^{-1} \left(\frac{(\vec{a} * \vec{b})}{\|\vec{a}\| * \|\vec{b}\|} \right) \qquad (9)$$

SAM classifier was processed with the following parameters (Table 4).

Classification used single threshold for all classes. Value is 0.100 and given in radians. This is the maximum angle between the end member spectrum
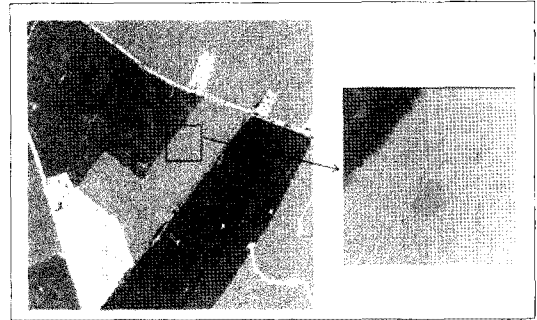

Fig. 4. An example of ground truthing point in soybean area

vector and the pixel vector. ENVI's SAM classifier does not classify the pixels that have an angle larger than this threshold value (ENVI, 2005).

1) Ground truthing and testing points

Ground truthing was carried out in 154 locations and the locations were marked. Ground truthing points are described in polygon shapes, which range from 5 to 929 pixels. Figure 4 shows one example of ground truthing point in soybean area.

2) Accuracy assessment

The accuracy assessment was based on whether the majority of classed pixels in a 3×3 pixel window, centered on a ground truth site, agreed or not. Thus, if five or more pixels were classified as corn, and ground truth indicated corn, then the majority criterion was satisfied and "corn class" would be considered correct for that site.

Accuracy check was carried out in 200 testing points to estimate the accuracy of each classification (Table 5 and 6). The accuracy testing points were distributed randomly in the classified image. Once all of testing points were checked, the producer and user accuracy of the individual class as well as the overall accuracy of the classification were calculated. Using the data in Table 5 and 6, user and producer accuracy percentages can be calculated for each class separately, as given in Table 7 (Jensen, 1996). The

Table 5. Accuracy assessment table for support vector machine classification. A: Classified, B: Reference

A \ B	Corn	Forest	Soybean	Urban built	Water	Wheat	Rural barren	Dry herb	Row total
Corn	31	7	10	1	0	0	4	3	56
Forest	9	32	6	3	0	2	0	5	57
Soybean	2	4	28	1	0	0	0	0	35
Urban built	0	0	0	13	0	0	3	0	16
Water	0	0	0	0	3	0	0	0	3
Wheat	0	0	0	6	0	8	0	0	14
Rural barren	0	0	0	1	0	0	2	0	3
Dry Herb	0	1	0	7	0	0	0	8	16
Total	42	44	44	32	3	10	9	16	200

Table 6. Accuracy assessment table for spectral angle mapper classification. A: Classified, B: Reference

A \ B	Corn	Forest	Soybean	Urban built	Water	Wheat	Rural barren	Dry herb	Row total
Corn	41	3	3	2	0	0	1	7	57
Forest	4	28	13	0	0	0	0	3	48
Soybean	0	1	39	0	0	0	0	0	40
Urban built	0	0	0	6	0	0	4	0	10
Water	0	0	0	0	6	0	0	0	6
Wheat	0	0	0	1	0	5	1	1	8
Rural barren	0	0	0	1	0	3	5	2	11
Dry Herb	0	4	0	2	1	1	4	8	20
Total	45	36	55	12	7	9	15	21	200

Kappa statistics for each classification was also calculated (Table 7).

The variance of Kappa can be calculated as follows:

$$\sigma_K^2 = \frac{1}{N} \left(\frac{T(1-T)}{(1-U)^2} + \frac{2(1-T)(2TU-V)}{(1-U)^3} \right.$$

$$\left. + \frac{(1-T)^2(W-4U)^2}{(1-U)^4} \right) \qquad (10)$$

where

$$T = \frac{\sum x_{ii}}{N} \;;\; W = \frac{\sum\sum[x_{ij}(x_j + x_{+i})]}{N^3}$$

$$V = \frac{\sum[x_{ii}(x_i + x_{+i})]}{N^2} \;;\; U = \frac{\sum x_i + x_{+i}}{N^2}$$

where

N = total number of ground truthing points

X_{ii} = number of correct classification in the specified class

X_{i+} = row total in error matrix for specified the class

X_{+i} = column total in error matrix for the specified class

Using the Equation 10 and data in Table 5 and 6, Kappa (KHAT) variance can be calculated for each classifier as follows.

$\sigma^2(K_{SVM}) = 0.002217$ for SVM classifier

$\sigma^2(K_{SAM}) = 0.001829$ for SAM classifier

Kappa statistics is often used to compare the results of multiple classifications (Congalton 1991). Kappa and its variance $\sigma^2(K)$ have calculated for each classifier. Using these two statistics, a test statistic (Table 8) is calculated as follows:

$$Z = \frac{K_1 - K_2}{\sqrt{\sigma_{K_1}^2 \, \sigma_{K_2}^2}} \qquad (11)$$

This test statistic follows as Gaussian (normal) distribution and can be used to determine whether

Table 7. Accuracy assessment values for SVM and SAM classification

Classes	Accuracy of SVM		Accuracy of SAM	
	User	Producer	User	Producer
Corn	55.4%	73.8%	71.9%	91.1%
Forest	56.1%	72.7%	58.3%	77.8%
Soybean	80.0%	63.6%	97.5%	70.9%
Urban built	81.3%	40.6%	60.0%	50.0%
Water	100%	100%	100%	85.7%
Wheat	57.1%	80.0%	62.5%	55.6%
Rural barren	66.7%	22.2%	45.5%	33.3%
Dry Herb	50.0%	50.0%	40.0%	38.1%
Accuracies	Overall accuracy = 62.5% Kappa = 0.54		Overall accuracy = 69.0% Kappa = 0.62	

difference between the two classifications is significant or not. Significance at 95% is obtained by comparing the Z-score to the equivalent value (1.96) from the normal tables. If the Z-score is greater than 1.96, the classification accuracy results are significantly different (Table 8). The normal tables can also be used to test significance at other levels (e.g., 90%, 99%) as desired.

5. Results and Discussion

SAM was found to produce more accurate classification (69.0%) than SVM (62.5%) (Table 7). However, both classification results were low. Major factor caused the accuracy to be lower is that study area is very complicated itself. Urban and rural areas mixed together in the study area. That makes difficult to divide the study area into two pieces which are urban and rural. In the similar studies that are cited in the manuscript, usually unmixed images were used for classification. Therefore, classification result was higher. For instance, Liu *et al.*, (2006) tested SVM and SAM classifier in only urban area which is taken over the Washington, DC mall. Xiaomei *et al.*, (2009)

evaluated the response of both classifiers to noises and uncertainty in original hyperspectral image of rural area. Also, few classes were included (dry herbaceous and rural barren) which are very complicated to be classified well. Dry herbaceous area is similar to urban built area in terms of spectral information and color code. Hence, dry herbaceous area was not classified well. According to the accuracy assessment table, more than 50% of dry herbaceous area was misclassified as other classes (especially as urban area). Also dry herbaceous is located on the agricultural area mixed with single signature and it is the dried part of agricultural area. Some area which has little dry herbaceous, mostly misclassified as dry herbaceous class.

In both classifications the water category was classified well with similar user accuracies. In the case of forest, the user and producer accuracies of SAM were better (58.3, 77.8%) than SVM (56.1, 72.7%) respectively.

As far as agriculture crops are concerned, user and producer accuracies of corn and soybean were better in SAM than SVM. But, wheat was classified with 80.0% producer accuracy in SVM which is better than SAM with 55.6%. In the case of user accuracy of wheat, SAM classified better (62.5%) than SVM (57.1%) and in the case of wheat it was vice versa (Table 7). In case of dry herbaceous, user and producer accuracies were same (50.0%) and better than SAM (40.0, 38.1%).

SVM classified the remaining two classes (rural barren and urban built) with higher percentage of user accuracies than SAM. But SAM classified with high percentage of producer accuracies than SVM in these classes. Among the 8 classes, only water was classified with more than 80% user and producer accuracy in both classifications. Rural barren in SAM and SVM, dry herbaceous in SAM were classified with less than 40% producer accuracy. Rural barren and dry

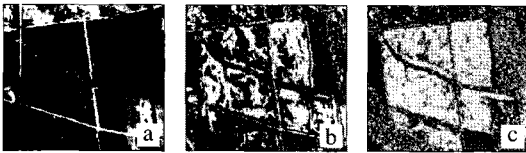Fig. 5. Portion of corn area. a) Image of study area b) Image classified by SVM c) Image classified by SAM.

Fig. 6. Portion of soybean area. a) Image of study area b) Image classified by SVM c) Image classified by SAM.

Fig. 7. Portion of urban built area. a) Image of study area b) Image classified by SAM c) Image classified by SVM.

Fig. 8. Portion of rural barren area. a) Image of study area b) Image classified by SAM c) Image classified by SVM.

Fig. 9. Portion of dry herbaceous area. a) Image of study area b) Image classified by SAM c) Image classified by SVM.

herbaceous in SAM were classified with less than 50% user accuracy. Overall, SAM performed well compared to SVM in Kappa statistics also (Table 7).

According to accuracy analysis, SAM classified better for a single signature such as corn, soybean and wheat area. Especially for corn and soybean, SAM performed much better than SVM (Fig. 5 and 6). Whereas, SVM classified single signature area mixed with other classes such as soybean, forest and dry herbaceous. For both classifiers, forest area was mixed with soybean and corn area, since spectral and color code are similar.

However, SVM was better for classes of mixed signatures such as urban built, rural barren and dry herbaceous area (Fig. 7, 8 and 9). Naturally, dry herbaceous and rural barren areas exist with forest and agriculture. Urban built area is one of the most difficult classes to classify accurately when it is located along with forest. SAM misclassified such mixed areas in some area (Fig. 8).

Shadow is very particular case, since it is not a single class. Mostly, SAM gave better classification in areas with shadow effects than SVM. In some areas, SAM misclassified shadows, while SVM classified as water or soybean.

From the Table 7, overall accuracy of SAM is

Table 8. Hypothesis test for comparing two classification results

Classifier	Kappa	Kappa variance	Z-score
SVM	0.54	0.002217	1.2574
SAM	0.62	0.001829	

more than SVM. It appears that using spectral information in image classification shows more accurate result. Some studies proved that using spectral knowledge into multispectral classification yields better results (Mercier, 2003).

Kappa is the statistical measure of inter-rate agreement for qualitative assessment in classification accuracy. The kappa statistics shows that both classifiers have performed well. However, the SAM (0.62) classifier shows little bit better result than SVM (0.54). In case of SAM, it gives substantial agreement, whereas SVM performed with moderate agreement in accuracy of classification.

Hypothesis test was calculated for comparing the results of two classifiers (Table 8). This test produces

Fig. 10. a) High resolution image of study area.
(Bands: 2, 5, 11 in BGR)
b) Classification result by SAM classifier
c) Classification result by SVM classifier

the difference between the two classifications. From the Table 8, Z-score is less than 1.96, consequently two classification accuracy results are not significantly different.

6. Conclusion

Classification of hyper spectral high resolution image based on two classification (SVM and SAM) algorithms was tested for their suitability. Based on the results, SAM is found to classify more accurately than SVM. As far as processing time is concerned, SAM produces outputs sooner than SVM. These conclusions are based on the present study. Therefore further studies are needed to ascertain these findings with diverse images from other satellites and many land use classes.

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