Classification of Hyper spectral Image Using Support Vector Machine and Marker-Controlled Watershed

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Abstract— *This research discuss the classification method observed which combined spatial information and spectral. There are three steps in the technique applied in this research. First, conduct the classification based on pixels hyperspectral image using suport vector machine (SVM). Second, the spacial contextual is used to rise the clasification result accuracy through the segmentation of hiperspektral image using the marker-controlled watershed method. Third, classsification based on pixel and image segmentation on the first step and the second, combined the result to aim the last map classification using the majority vote approach. The result finding obtained by using the hyperspectral image Aviris Indian Pines show the accuracy improvement compared with the classification using only the spectral information.*

Keywords—*Classification, hyperspectral image, marker-controlled watershed, support vector machine.*

I. INTRODUCTION

Image segmentation is an operation which aims to partition an image into a different region of cluster, whereas included the homogenity elements for several fitur such as: spectral/colour, texture, shape and others. Segmentation and image classification is the first step in a acquisition process (image analysis). This process was part of low level task which further used on the next process; the high level processing and on the application there were several sector; remote sensing, medical application, video coding, company automation, and many others [1] [2].

Remote sensing image classification was one of common application related to the segmentation based on spectra/color, textur, and shapes. Classification belongs to a labeling process of pixels from the image remote sensing intoa ground cover or various class through each of class characteristic. The numerous source of information mostly used to classify were the spectral characteristic from those single spectral [3]. Another function of image remote sensing is the spectral characteristic and class information from the nearby location of each pixels, named with the spatial information for that pixels. Spatial information explain attribute statistically from various kind of ground cover.

The problem with the previous multispectral / hiperspectral image classification has been solved by different approach. For example, several machine learning technique and image processing has been implemented to extract the well-suited information out of hyperspectral data during this last decade [4]. In a contexts supervised classifications, it is a real challenge with the fact of highly needed the data volume with considerably high dimention (with the limitation of training sample). In other words, with the small number of training sample and abundant of fitur number in a remote sensing, the estimate realibility class parameter statistically is a strongly difficult matter. As a result,with the restrictred training cluster, the accurate classification tends to decrease while the amount of fiture increase. This effect is well-known as the Hughes effect [5].

Remote sensing image classification based on spectral using the information spectral from each pixels to classify the suitable pixels by means of pattern recognition method. This classification technique could catch the spectral diversity of the different kind of ground cover. A set of method pattern applied on image remote sensing classification included the observed approached by the training sample and unobserved approach without training sample. The benefits for image classification based on spectral; it could be directly applied on the pattern recognition from one vector signal from each pixel. This method is fast and the classification model was not complex compared by combining spatial information into the classification. While the disadvantage using this classification based on spectral was the restricted accurate of classification and lack of the entangled spatial information.

To solve the weakness of image remote sensing based on spectral, some image classification technique based on spectral-spacial was built, for instance; first, cluster based on the classifier development based on spectral-spasial, which combine the related contextual information class during the classification. The Model Support Vector Machine (SVM) has became part of this group. Second, cluster based on additional fiture evocation to represent the spatial informatio generally. Those fitures will be merged simultaneously with the genuine spectral image and will be used as a input of classifier to obtain the thematic map. On a related class with the contextual information on a real image, those class will merged the labels from the nearby pixels into the classification. If the contiguous pixels will be classified into a certain pixels having high probability make it into the same class. Knowledge from the adjacency relation is an important information source, especially for high spasial image resolution, whereas this can not be exploited into a spectral based classifier in ordinary and traditionally. This spatial information could rise the thematic map into assistance of pixel labelling mistake removal individually which have the possibily resulting noisy data or the unusefull classificator appearance.

The purpose of this research was to increase the classification accuration through the merged of marker-controlled watershed and support vector machine (SVM). This research aims to solve the problem in segmentation and the classification of remote sensing hyperspectral image.

II. RESEARCH METHOD

The methodology applied in this research for the hyper spectral image which classified based on spatial information and spectral from those image using the marker-controlled watershed and support vector machine (SVM). The purpose was to gain a better classification accuracy compared by using the spectral information without involving the spatial information. To obtain this, it could be started by conducting the features extraction by means of reduce the real hyper-spectral image data dimension using the combination method of minimum noise fraction (MNF) and the principal component analysis (PCA). The classification process using the spectral information and image segmentation using the spatial information separately. The result of those two process further will be combined by a certain combination rule which is called majority vote [6]. The detail diagram of remote sensing of hyper-spectral image classification based on the combination of the spectral information and spatial as shown in the Figure 1.

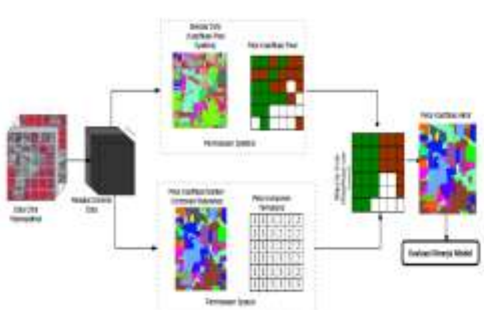

Figure 1 : Scheme of remote sensing of hyperspectral image classification based on the combination of the spectral information and spatial

In this experiment use image scene from Airborne Visible/Infrared Imaging Spectrumeter (AVIRIS) sensor. AVIRIS sensor operation in visible spectrum, near and mid infrared with distance wave range from 0.4 μm to 2.4 μm. Sensor system have 224 band with spatial resolution 20 m. Indian Aviris image taken in 1992. The real image with the specification of 45 x 145 pixel. THe image contain 202 spectral band (after reducing the spectral band contain the noise and water absorption),s o this image only consist of 190 spectral band used in this research. The wave length were between 0.4 to 2.5. This image contain 16 corresponding class [7]. Table 1 show the class information and sampel of ground truth labelling hyperspectral image data of Aviris Indian Pines.

Table 1: Eigenvalue statistic and the cumulative percentage of covariance matrix on the transformation combination MNF PCA MNF Aviris Indoan Pines Image

PC #	Aviris Indian Pines	
	Eigenvalue	Cummulative variance(%)
1	46.54	27.30
2	19.34	38.64
3	14.81	47.33
4	12.75	54.81
5	11.92	61.80
6	8.96	67.05
7	8.12	71.82
8	6.51	75.64
9	5.84	79.06
10	4.79	81.87
11	3.35	83.83
12	3.09	85.65
13	2.48	87.10
14	2.14	88.35
15	2.01	89.53
16	1.93	90.66
17	1.86	91.75
18	1.84	92.83
19	1.81	93.89
20	1.76	94.93
21	1.75	95.95
22	1.74	96.97
23	1.73	97.99
24	1.72	98.99
25	1.71	99.00

III. RESULT AND ANALYSIS

This chapter will explain the result finding of the research. THe analysis and the discussion will be detailed explain to show that there was an increasing accuracy of image classification resulting by the use of data dimention reduction method, the measurement of training sample, and the use of spatial information combined with the spatial information.

A. *Data Dimention Reduction*

The reduction of data dimension in this research used the combination of MNF and PCA method [8]. This method was applied by conducting the dimensional reduction process first before starting the reduction process using PCA. The method of data dimension intrinsic determination were used to determine its effectivity in hyperspectral data cluster [9]. PC could be obtained by calculating the correlation of matrix value, afterwards the eigenvalue will be resulted from those image data. Figure 2 show the graphic 25 eigenvalue, the combination of the first MNF and PCA from the correlation matrix AVIRIS Indian Pines data image, while in the table 2 it is shown the accumulative percentage of eigenvalue, as well as the eigenvalue from 25 eigenvalue The combination of the first MNF & PCA combination from the data image, respectively.

Based on the scree test criteria for the Aviris Indian Pines images, 2 principal component were retained, it can be seen from the curve which indicate the even line after 2 component. While using the criteria of cumulative variance, at least 90% total variance was needed to retain the component. Hence, there would be 15 first component of PC. From those two method of intrinsic determination of dimension reduction on hyper-spectral image it could be seen that the result of the retained component will be different, especially when the data was noisy.

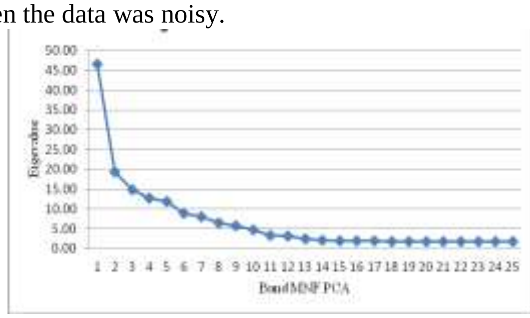

Figure 2: Graphic scree 25 eigenvalue the combination of the first PCA MNF using the covariance

B. *Classification Using SVM*

The spectral classification in this research was the pixel-wise classification, carried out through the support vector machine (SVM) method. In this research, the kernel will be compared for the data cluster classification with limited training sample. The data used in this research was the high-resolution data. The hyper-spectral data image applied in this SVM kernel test was the Aviris Indian image. The image of Aviris Indian Pines was the hyper-spectral image with the 145x145 pixel and consist of 202 spectral band. The training data sample and testing will be shown in Table 1. The smaller data training will be built by means of choosing randomly from the training sample cluster respectively, then it will be composed as 5%, 10%, 15%, 20%, 60%, 80% dan 100%*(all)*from pixels. Further, two kinds of input feature; the original data and the data reduction will be constructed for the training sample poll and applied to train a certain SVM classifier which consist of two kinds of kernel; polinominal and RBF. SVM has been trained by each part of the training and then evaluated by the cluster testing. During the training process, the kernel parameter γ and the C penalty adapted to maximize the OA estimation. From this research, the kernel parameter was $\gamma=0.125$ and penalty C=0.125 obtained by means of fivefold cross validation. Figure 3 show the classification result using the SVM classifier and RBF kernel and polynomial where each of the training sample taken by 10%. While Table 2 indicate the whole accuracy value (OA), average accuracy (AA), and Kappa index (γ) Aviris Indian Pines image used in this research. As for the value of OA, AA and Kappa index for the whole sample will be shown in table 3, whereas the accuracy of value graphic will be shown in the Figure 4

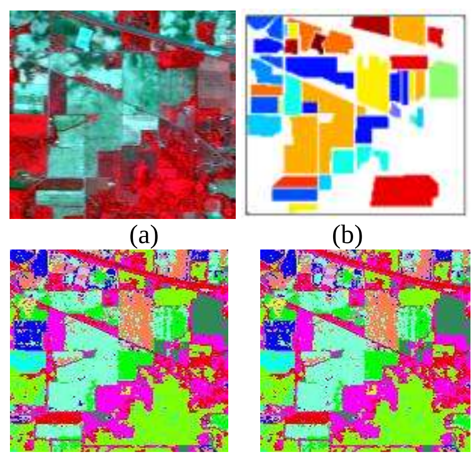

Figure 3 : The SVM classification result (a) Image Composite band (57, 27, 17), (b) classification with RBF kernel, (c) polynomial kernel by 10% of training sample of each class.

Table 2 : The percentage of SVM classification accuracy using polynomial kernel and RBF Gaussian on the extracted feature from Aviris Indian Image.

Image	AVIRIS Indian Pines				
Jenis Fitur	Jumlah feature	Kernel Polynomial		Kernel RBF Gaussian	
		10%	All	10%	All
All Band	202	74.40	94.27	74.87	94.12
PCA	10	79.86	90.58	79.87	91.09
MNF	10	91.63	96.06	91.62	93.56
MNF+PCA	10	91.78	96.07	91.63	98.09

Table 3: The percentage of classification accuracy using polynomial kernel and RBF Gaussian on the extracted feature on Aviris Indian Pines Image.

Number		1	2	3	4	5	6	7
Training Size		5%	10%	15%	20%	60%	80%	All
RBF Gaussian	OA	69.2	74.9	79.7	83.1	91.1	92.8	94.1
	AA	48.1	53.2	62	66.8	88.7	90.5	93.1
	κ	0.64	0.71	0.77	0.81	0.9	0.92	0.93
Polinomial	OA	69.8	74.4	80	83.1	91.6	92.9	94.3
	AA	48.3	52.4	62.4	66.8	87.7	90.4	94.4
	κ	0.65	0.7	0.77	0.81	0.91	0.92	0.94

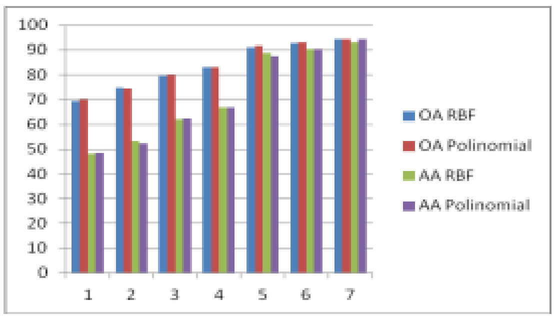

Figure 4 : The Overall Accuracy (OA) value graphic and Accurate Accuracy (AA) classification based on spectral-spatial by SVM polynomial kernel and RBF Aviris Indian Pines data images.

It can be seen from the figure 4 that the OA value, classification using SVM kernel RBF was higher than using kernel polynomial. It is indicated on the sample with the 10% measurement from the whole labelled sample. From this result, hence the image classification that will be shown in this paper was the classification using SVM kernel RBF by the sample of 10%. In figure 5, the classification result of Aviris Indian Pines image using SVM kernel RBF was disclosed, whereas the standard six of the sample was 10%. The dimensional data reduction method was using PCA, MNF and MNF PCA combination.

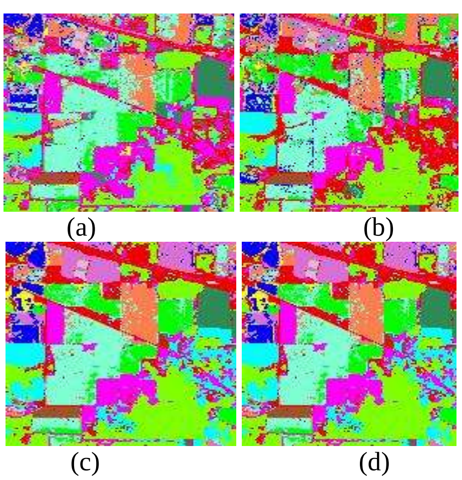

Figure 5: The classification result of Aviris Indian Pines using SVM kernel RBF with 10% of each class training sample on (a) the original image, (b) the PCA dimensional reduction method, (c) MNF method, (d) The combination method of MNF & PCA.

C. *Segmentation Using Marker-Controlled Watershed*

Different approach from the hyperspectral image watershed transformation were tested in this research. The watershed segmentation displayed on gradient function which can be obtained by four steps.

1. Band 60 (single band) : A Beucher gradient morphology calculated on one band. Band number 60 was chosen but the same result will occured for other unnoisy band. The morpholohgical operation conducted on 3x3 square penstructure element E (center from E in a square centre)
2. Band1PCA; Morphology Gradient for band PC1 from PCA transformation counted, then conduct the morphological operation as stated in the first step.
3. Band1MNF : The gradient morphology for band MNF1 from MNF transformation calculated, then conduct the morphological operation as in the first step.
4. Band MNFPCA: Gradient morphology for band MNFPCA1 from the combination transformation of MNF and PCA was calculated, then conduct the morphological operation as in the first step.

The four gradient of Aviris Indian Pines image which is obtained its object boundary defined through all the image gradient. Most of spatial structure acknowdledge from the single band whereas in this research, the single band used on the original image using the band 60. Whereas on the extracted feature data image was used the PCA method, MNF, and the combination of MNF PCA. The band which is used was the band 1.

Further, the four image gradient obtained, was directly used to conduct the watershed transformation process using the Vincent and Soile algorithm (1991) [10]. The result of this segmentation using the watershed transformation directly without conducting other process except the image gradient calculation will result the segmentation map which is over segmentation. To avoid this, the marker-controlled watershed could be used. Figure 6 show the result of Aviris Indian Pines marker-controlled watershed using (a) band gradient 60, (b) PCA band 1, (c) MNF band 1, (d) combination of MNF PCA band 1

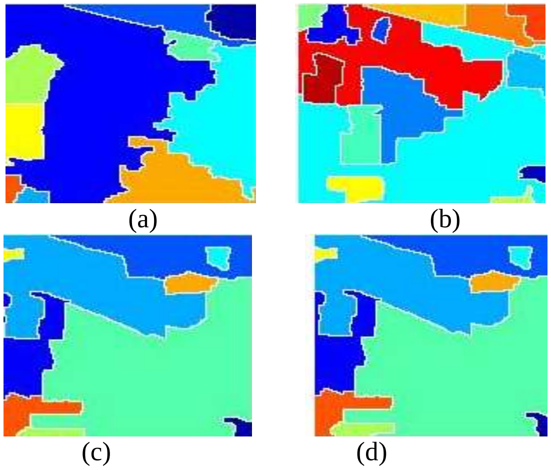

Figure 6 : the result of Aviris Indian Pines image marker-controlled watershed through (a) the Gradient band 60, (b) PCA band 1, (c) MNF band 1, (d) Combination of MNF PCA band 1

D. ***Segmentation Using Marker-Controlled Watershed***

The classification of hyperspectral image which implicate the spectral and spatial information in this research was conducted using the majority vote [12]. The image segmentation conducted using the watershed transformation to integrate the spatial information obtained from the image segmentation result by the spectral information on the spatial-spectral image classification process to gain the accuracy qualitatively from the watershed segmentation, the obtained segmentation map could be combined into a spatial-spectral classifier combination

The spatial-spectral classification approach using the majority vote were conducted as follows; First, a pixel based classification, which only based on spectral pixel information and a certain segmentation displayed separately. In this research, the pixel based classification using SVM method, while the image segmentation using marker-controlled watershed. Second, for each region on segmentation map used the marker-controlled watershed, every pixel were included in a class with the most frequency between this region. The result of the Aviris Indian Pines image classification combined with kernel RBF Gaussian SVM 10% training sample each class and watershed Band1 MNFPCA were used the rule of Majority Vote as shown in the Figure 7. Meanwhile, the whole accuration value using the majority vote on Aviris Indian Pines shown in the Table 4.

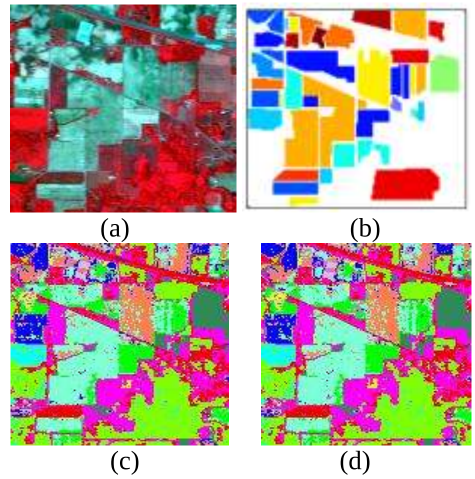

Figure 7 : the image classification map of Aviris Indian Pines combined with kernel RBF Gaussian SVM 10% of each class training sample and watershed Band1 MNFPCA using the majority vote rule.

Table 4: The Overall Accuracy (OA) on the image classification of AVIRIS Indian Pines

Metode			OA	AA	K
SVM			78.18	85.96	75.34
SVM	MV	No CMW	86.64	86.96	83.97
SVM	MV	CMW	86.64	91.60	84.82

IV. CONCLUSIONS

In this paper, a classification scheme based on the new spectral-spatial using the marker-controlled and support vector machine were introduced. Those method was based on the formation of a certain marker through the image morphological reconstruction and applied for the preceded process before conducting the watershed transformation. It was carried out to avoid the over segmentation if the watershed transformation was directly used in a image segmentation. The data dimension reduction could be done by using the combination of MNC PCA as the feature of extraction process before conducting the classification by SVM kernel. The combination of spectral and spatial information could be gained separately using the majority vote rule. From the research result using the suggested method in this research, it can be concluded that the addition of spatial information into a spectral information on the classification process will enhance the overall accuracy result on remote sensing hyperspectral image classification.

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