An improved classification of hypersepctral imaging based on spectral signature and Gray Level Co-occurrence Matrix

Fedia Ghedass[1] and Imed Riadh Farah[1,2]

1. RIADI Laboratory, National School of Computer Science

Universi0ty of Manouba, Tunisia

2. Telecom_Bretagne, Departement ITI, Brest, France

ghedass.fedia87@gmail.com, riadh.farah@ensi.rnu.tn

ABSTRACT. Hyperspectral imaging (HSI) has been used to perform objects identification and change detection in natural environment. Indeed, HSI provide more detailed information due to the high spectral, spatial and temporal resolution. However, the high spatial and spectral resolutions of HSI enable to precisely characterize the information pixel content. In this work, we are interested to improve the classification of HSI. The proposed approach consists essentially of two steps: features extraction and classification of this data. Most conventional approaches treat the spatial information without considering the spectral information contained in each pixel, for that, we propose a new approach for features extraction based on spatial and spectral tri-occurrence matrix defined on cubic neighborhoods. This method enables the integration of the spectral signature in the classical model for calculating the co-occurrence matrix to result the 3D-Gray Level Co-occurrence Matrix (GLCM). Concerning the classification step, we are mainly interested in the supervised classification approach. We used the Support Vector Machine (SVM) allowing classification without using a dimensionality reduction.

We will consequently test the proposed approach on an IHS that was recorded by an AVIRIS sensor. It's an Indiana Pines scene which is a vegetation zone captures in north-western Indiana. It's composed of two spatial dimensions of size 145X145 pixels and with spatial resolution of 20m per pixel, and a spectral dimension with 220 bands. The choice of this image is melted by the existence of a ground truth and its permanent use in all IHS analysis problems. The experimental results indicate a mean accuracy values of 70.73% for VGLCM. It shown the robustness of our perspective approach better classification rate and high accuracy.

KEYWORDS: Hyperspectral imaging ; feature extraction ; classification ; spectral-spatial information ; SVM.

Résumé. Les images hyperspectrales suscitent un intérêt croissant depuis une quinzaine d'années. Elle s'est utilisée dans divers domaine tel que la géologie, l'écologie, astronomie et le militaire. L'IHS est caractérisé par sa richesse en information spectrale, spatiale et temporelle. Dans notre étude, on va s'intéressé seulement aux informations spectrales et spatiales. Le traitement et l'analyse des IHS est une tache très difficile, cela est du au grand volume données de ce type d'image. De ce fait, l'approche proposée comporte deux phases : la première consiste à l'extraction des informations et la deuxième c'est la classification. La plupart des approches traditionnelles traitent l'information spatiale sans prendre en considération l'aspect spectral. Pour cela, nous allons utilisés une nouvelle méthode d'extraction des informations qui prend en compte à la fois les deux types d'informations spectrales et spatiales, cette nouvelle méthode est une extension de la matrice de co-occurrence du niveau 2D au 3D. Elle combine à la fois la signature spectrale de chaque pixel ainsi que la matrice de co-occurrence calculé à ce niveau. Pour la deuxième phase de notre processus d'analyse : la classification, nous allons mettre l'accent sur la classification supervisée et plus précisément sur la méthode Machine à support vecteur (SVM). Nous allons par suite, tester l'approche proposée sur une image hyperspectrale qui a été enregistré par un capteur AVIRIS. Elle présente un scéne d'INDIAN PINES qui est une zone de végétation, capturée sur le site de test indienne pines dans le nord-ouest de l'Indiana. Notre image est composée de deux dimensions spatiales de taille 145X145 pixels une résolution spatiale de 20m par pixel, et une dimension spectrale de 220 bande. Le choix de cette image est fondu par l'existence d'une vérité terrain ainsi que son utilisation permanente dans tous les problèmes liés à l'analyse et l'interprétation des IHS. Les résultats expérimentaux ont montrés la robustesse de notre approche de point de vue meilleure taux de classification et une grande précision.

MOTS CLES: Image hyperspectrale ; extraction des informations ; classification ; Information spectro-spatiale ; SVM.

1. Introduction

Hyperspectral remote sensing plays an important role in land use/cover classification and mapping [7]. For that, the interest of IHS data has been constantly increasing during the last years. They provide a more detailed view of the spectral properties of a scene and permit a more accurate discrimination of objects as color images, or even multi-spectral images. Although the potential of hyperspectral technology appear relatively large, analyzing and processing these large volumes of data remain a difficult task and operation now presents a challenge in terms of interpretation. Indeed, the IHS is a well-suited technology for accurate image classification. However, the large amount of data (bands) complicates the image analysis. Most classification techniques proposed in the literature treat each pixel independently, without considering the spatial information [8]. However, recent image processing research has highlighted the importance of incorporating the spatial context in the classifiers.

In fact, to be able to exploit hyperspectral data, classification is an important step. It can be done on a supervised or unsupervised manner. Thus, in this paper, we are interested in the supervised classification approach for IHS data. An extensive literature is available on the classification of IHS such as: Maximum likelihood or Bayesian estimation methods, decision trees, neural networks, genetic algorithms and kernel-based techniques [1]. One of the most popular classification methods is the Support Vector Machine (SVM). The second step in the process of analyzing IHS is the features extraction [2].

This work aims also to conduct a comparative study of several classification methods based primarily on the type of information to be considered for each classifier in order to study the complementarily of the spectral and spatial information and their contribution in a classification step. For that, we will exploit two types of information such as the spectral and spatial information. Therefore, we will use the spectral signature of each pixels of image as spectral information. However, we will extract the co-occurrence matrix to obtain the spatial information. Finally, our approach consists on combining these two types of features to get the 3D co-occurrence matrix. To exploit these data, the classification step is considered as an essential step. The remainder of this paper is divided into 4 sections. In section 2, we will describe the feature extraction and the novel methodology based on combining spectral signature and the GLCM, and the classifiers used. In section 3, we show the developed approach. And finally in section 4, we show the experimental results obtained by our approach and conclusion for this work followed by some perspectives.

2. Hyperspectral Imaging analysis

In this section, we, present:

- An overview of different methods of features extraction and its disadvantages;
- The classifier that we will used in this work;

2.1. Feature extraction

Before the classification, feature extraction is an important processing procedure. In the case of hyperspectral data, it is necessary to use attributes that are not only able to characterize the spectral appearance, but also taking into account the spatial information. The consideration of spatial information seems very useful in the case of complex classification problems where objects are discriminating spectrally very close. Feature extraction can be divided into two categories, spectral features and spatial features [15]. Recently, we are interested to combine both spectral and spatial information to improve classification accuracy.

2.1.1. Spectral feature extraction

In addition to the attributes directly related to the spectral signature of each pixel, there are several methods that also identify the spectral information contained in the hyperspectral image. For example, feature extraction is typically conducted for reducing the dimensionality of IHS. Usually, it can be obtained either by selection of the relevant bands [13] or by data projection in a new subspace [14]. Among the most used techniques, we find Principal Component analysis (PCA) [3], Maximum Noise Fraction (MNF) [4], Independent Component Analysis (ICA) [4] and Fisher’s Linear Discriminate Analysis (FLDA). These methods can provide more disadvantages like the loss of information that causes the precision rates less then when we used IHS without considering the DR procedure. The second disadvantage is that the non consideration of spatial information, each pixel will be treated without considering its neighborhood. We are interested in this work to use the entire hyperspectral image as a descriptor of spectral information.

2.1.2. Spatial feature extraction

The methods are intended to measure the spatial behavior of the neighborhood of a pixel. This measure can be derived from statistical processing, morphological or purely radiometric and must be calculated over all pixels in the image. Many approaches have shown that the textural features are the most methods used for characterization of spatial information [4], and commonly used as an index for feature extraction and image classification. Conventional texture analysis algorithms compute texture properties in a two-dimensional (2D) image space. They extracted text features of each band image alone, and then integrate all bands characteristics for further analysis. The methods ignored the fact that the hyperspectral data often has strong spectral correlation, and will lose lots of useful spectral information. This may work well in panchromatic (single band) images and multispectral imagery with limited and discrete spectral bands. This method has been widely used for target classification, image retrieval, etc.

2.1.3. Spectral-spatial feature extraction

In this case, we are interested to combine both, the spectral and spatial information. In the literature, we have two manners to do this combination: the first one consists in concatenation of two vectors of attributes, respectively spectral and spatial [5]. The second manner is to extract information based on higher order statistics for discriminating complex textures classes [6]. In recent years, 3D image formats have become more and more popular, providing the possibility of examining texture as volumetric characteristics. For that, it’s necessary to extend traditional 2D Gray Level Co-occurrence Matrix (GLCM) to a 3D form [9]. By using the method of texture features combined with spectral features, we can not only acquire different feature information of the target, but also can avoid the spectral phenomenon, which can improve the precision of classification.

The 3D-GLCM, named also Volumetric GLCM (VGLCM) texture can capture the relations between neighboring spectral bands. As shown in Fig. 1, the procedures for texture extraction by using 3D-GLCM and GLCM are different. The GLCM model uses a 2D moving window in 2D space. However, 3D-GLCM applies a moving box in 3D space to calculate the texture. For a hyperspectral image cube with n gray levels, the co-occurrence matrix, M, is an n-by-n matrix. Values of the matrix elements within a moving box, W, at a given displacement d = (dx, dy, dz) are defined as:

$$M(i,j) = \sum_{x=1}^{wx+dx} \sum_{y=1}^{wy+dy} \sum_{z=1}^{wz+dz} \begin{cases} 1, w(x,y,z) = i \text{ and } w(x+dx, y+dy, z+dz) = j \\ 0, otherwise \end{cases} \quad \textbf{(1)}$$

Where i and j are the values of pairwise pixels, and x, y, z represent the positions in the moving box. M(i,j) is the value of a 3D-GLCM element [9].

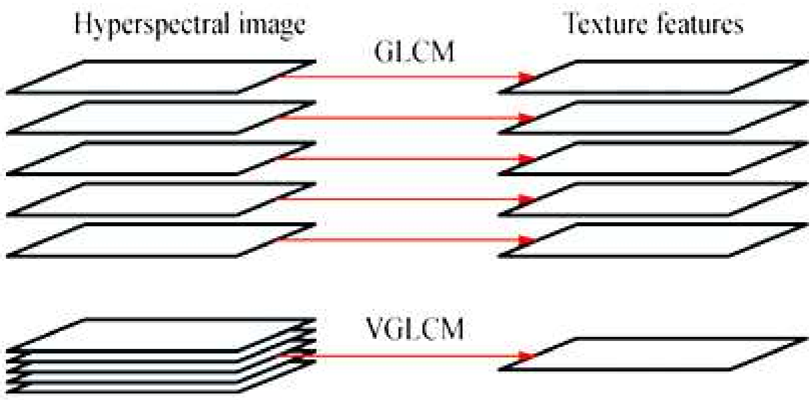


Fig.1. Texture computation of GLCM and VGLCM

Because not all of the statistical measures are suitable for describing the texture feature, we chose variance, contrast, dissimilarity, energy, entropy and homogeneity as the measurements to extract the texture features, Table 1.

Table1. Co-occurrence features

Feature	**Formula**
Entropy	$Entropy = \sum_i \sum_j C_{a,b} \log C_{a,b}(i,j)$
Energy	$Energie = \sum_i \sum_j C_{a,b}\,(i,j)^2$
Contrast	$Contraste = \sum_n n^2 \sum_i \sum_j C_{a,b}\,(i,j), \quad \lvert i-j \rvert = n$

Variance	$Variance = \left(\frac{1}{2}\right)[\sum_i \sum_j (i-\mu)^2\, C_{a,b} + \sum_i \sum_j (j-\mu)^2\, C_{a,b}]$
Homogeneity	$Homogeneity = \sum_i \sum_j (\frac{C_{a,b}}{1} + (\lvert i-j \rvert))$

3. Support Vector Machines (SVM)

Support vector machine is a learning system based on the statistical learning theory. This classification technique aims at finding a separating hyperplane that splits the input data space into two separate regions corresponding to the two classes defined in the discrimination problem. SVM do not require an estimation of the statistical distribution of classes to carry out the classification task, whereas it only defines the classification model by exploiting the concept of margin maximization by taking into account only few training pixels. SVM is an effective method of statistical learning theory, compared with the traditional classification methods; it is suitable for small samples learning, besides, it has better generalization ability and high efficiency for learning [16].

Support vector Machines performs the robust non-linear classification with kernel trick. It outperforms other classifiers even with small numbers of the available training samples.

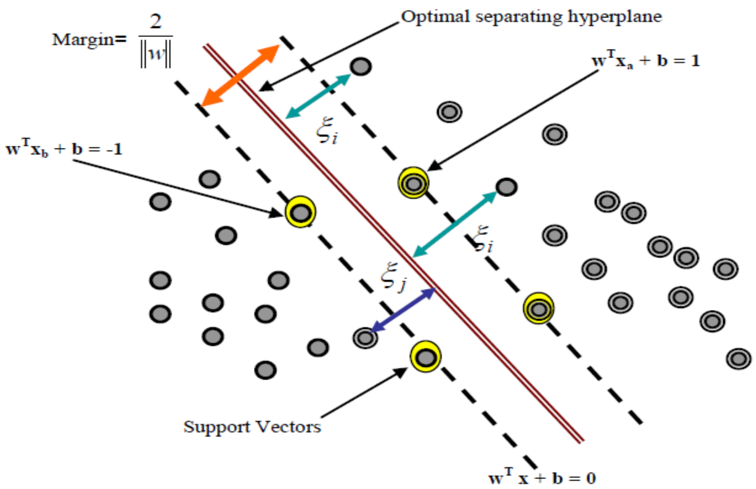


Fig.2 SVM Hyperplane

SVM is a supervised classification method. Several works have showed his effectiveness in land use classification for remote sensing images [10, 11]. SVM finds the separating hyperplane in some feature space inducted by the kernel function. For the given training set, the decision function is found by solving the convex optimization problem.

$$\max G(\alpha) = \sum_i \alpha_i - \left(\frac{1}{2}\right) \sum_{i,j} \alpha_i \alpha_j y_i y_j K(x^i, x^j) \qquad \textbf{(2)}$$

Where α is the lagrange coefficient and α ε [0, C], C is a positive constant that is used to penalize the training errors and K is the kernel used.

When optimal solution is found, the classification of a sample X is achieved by looking to which side of the hyperplane it belongs:

$$y = signe\ (\sum_i \propto_i y_i K(x^i, x) + b)\ \mathrm{b} \qquad \textbf{(3)}$$

We will use the Radial Basis Function (RBF) kernel in this experiment.

One against all (OAA) strategy is used while classifying the images. By which one class is separated from others. Thus the classes are separated hierarchically Fig.3.

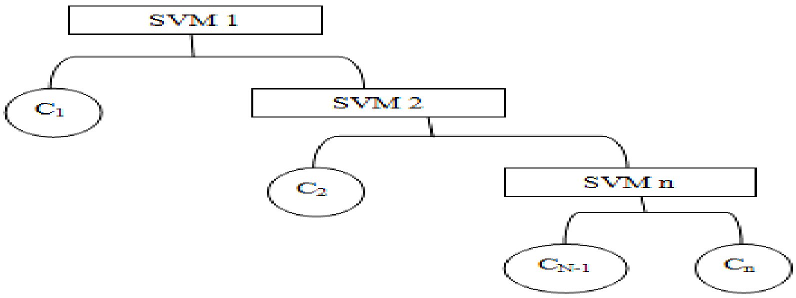


Fig.3 OAA binary hierarchical tree (BHT)

In remote sensing, for doing the step of classification, we will use a spectral database that can provide a source of reference spectra that can aid the interpretation of hyperspectral images. These libraries are available for public use. It contains several spectral signatures for different natural and artificial materials. The spectral signatures usually have the details and information needed to qualify and quantify the existing materials in the environment that’s why it is unique for each one. We distinguish specific spectral signature for each type of materials Fig.4.

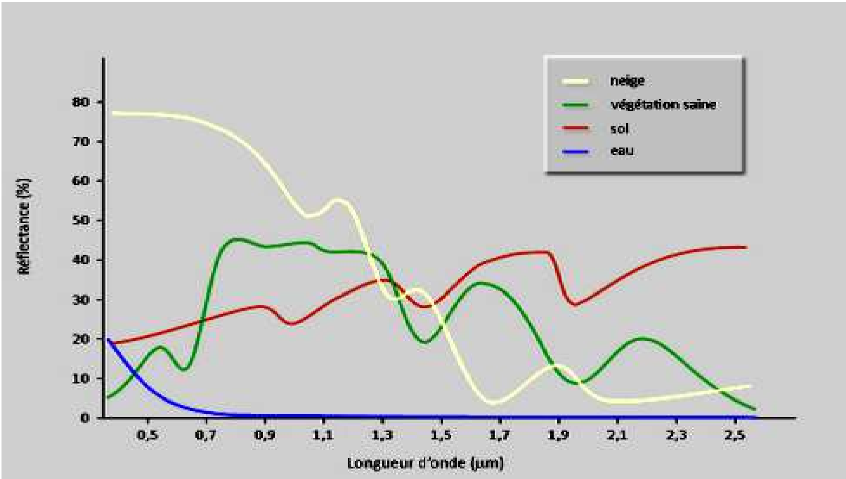


Fig.4 Spectral signature for different materials

The use of these libraries is important when we compare the spectral signatures obtained in our approach with the different spectral signature of spectral library.

4. Proposed approach

In this section, we introduce our approach for classification of hyperspectral imaging based on spectral signature and GLCM. The central idea is to integrate both the spectral and spatial information to obtain an accurate classification of IHS without using a dimensionality reduction. Our approach is based on two several steps:

The first step aims to characterize each pixel in the hyperspectral image to be used later for classification step. Here, we are interested to distinguish two types of feature: spectral and spatial information. In the other hand, we will fuse both spectral signature and the texture feature. The fused feature vectors are then used as inputs for support vector machines, and overall classification accuracy is used for performance evaluation. Three schemes, listed in table 2, are designed to validate that texture feature could increase classification accuracy. The detailed schemes are:

- Scheme I: spectral classification based on spectral signature
- Scheme II: spatial classification based on GLCM
- Scheme III: texture features fused with all of the bands of original data

Table 2 Feature schemes for hyperspectral image classification

	Classification with spectral data		Classification with spatial information
Scheme I	All bands		-
Scheme II	-		GLCM
Scheme III	All bands	+	GLCM

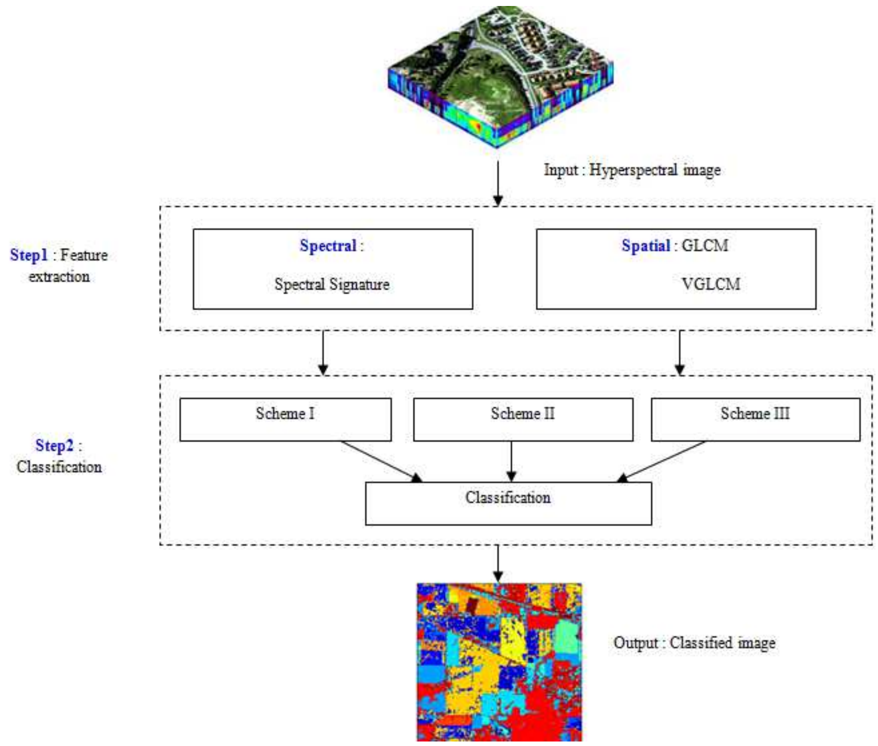
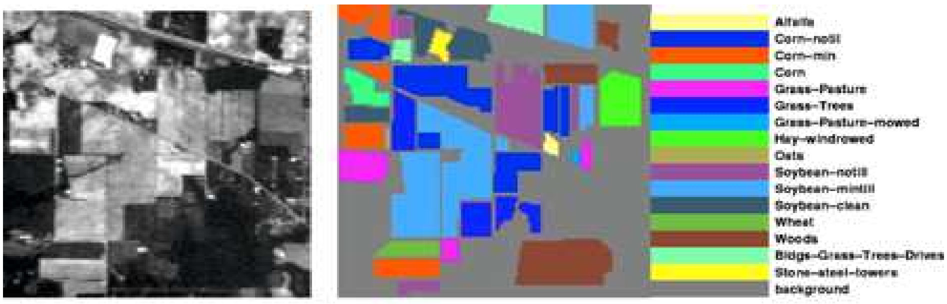


Fig. 5 Proposed approach

5. Experiments and results

To validate our approach, we used a hyperspectral image AVIRIS on the region Indiana Pine at north western Indiana, USA. It is composed of two spatial dimensions of size 145X145 pixels with spatial resolution of 20m per pixel and it contains 220 bands. The noisy bands (bands 104 - 108, 150 – 163, and 220) are removed so that 200 bands remained for the experiments. This hyperspectral imagery contains 16 land-cover classes and 10366 labeled pixels Fig. 6. Table 3 lists the number of labeled samples for each class [12]. We randomly chose 50 samples for each class from the reference image for training, except for the classes of "alfalfa", "grass/pasture-mowed", "oats", and "stone-steel towers". These classes contain a limited number of samples in the reference data, and, hence, only 15 samples for each class were chosen randomly for training. The remaining samples composed the test set.



(a) (b)

Fig.6 ground truth

Table 3 Number of samples in each cover class in the Indiana data set

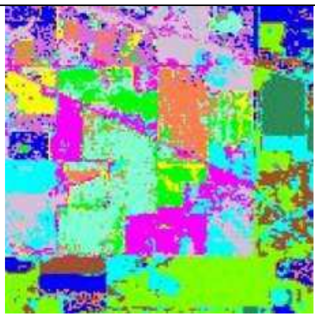
	Class	Samples
1	Alfalfa	54
2	Corn-notill	1434
3	Corn-mintill	834
4	Corn	234
5	Grass-pasture	497
6	Grass-trees	747
7	Grass-pasture-mowed	26
8	Hay-windrowed	489
9	Oats	20
10	Soybean-notill	968
11	Soybean-mintill	2468
12	Soybean-clean	614
13	Wheat	212
14	Woods	1294
15	Buildings-Grass-Trees-Drives	380
16	Stone-Steel-Towers	95

In this section, we present the result obtained by the developed approach for the IHS classification. We present, at the first time, a classification result directly exploiting the spectral signature of each pixel. Secondly, we present the results obtained using GLCM methods, and finally, we evaluate the proposed tri-occurrence attributes used in this case.

The table below shows the SVM classification results of the image shown above, with the same configurations of attributes in the previous section.

Table 4 Results of hyperspectral image classification

Features	Classification results	
Spectral signature		ACC= 67.83% Kappa= 0.57
Co-occurrence matrix (GLCM)		ACC=73.40% Kappa=0.74
Volumetric Co-occurrence matrix (VGLCM)		ACC=70.73% Kappa= 0.70

The classification map of the different features extraction is compared in table 4. In this data, only the spectral information cannot effectively discriminate between different information classes, resulting in an ACC = 67.83%. The exploitation of the GLCM texture can significantly improve the results and the increments of the ACC = 73.40%. It can be seen in the table above.

Volumetric texture features with spectral information derived from spectral signature were investigated in hyperspectral image classification. A comparison study between the GLCM algorithm and the VGLCM demonstrate that the first one is generally applied to a single band at a time, and then the second is applied to a moving box in 3D space, there by leading to more informative texture features. The experimental results demonstrated that by extracting texture features in 2D space, the classification GLCM outperforms that by extracting texture features in 3D space. This is due to the high dimensionality of our data. The spectral dimension of the pixels has little effect on the final classification accuracy. It is therefore sensible to appropriately reduce the spectral dimensionality.

The proposed method can provide accurate classification results for hyperspectral bands. Compared with the original spectral classification, the accuracy increments achieved by the VGLCM.

In this way, fig7 shows the classification accuracy of our approach. Than we distinguish that many classes obtained after doing the classification task have a high accuracy, comparing with the ground truth, which allows evaluating the performance of the used classification approach.

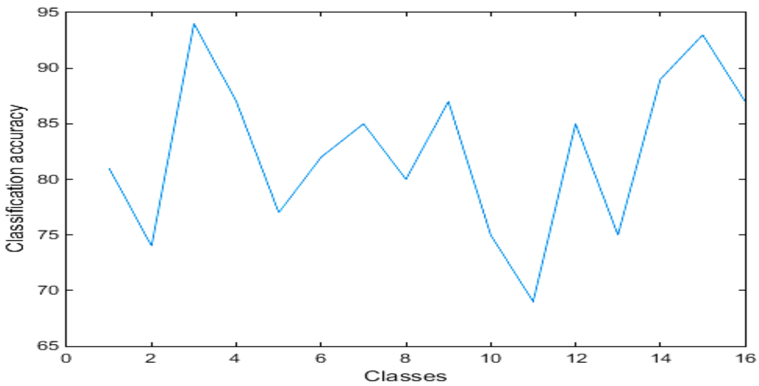


Fig.7. Classification result with SVM

A possible uncertainty for the proposed method refers to the selection of parameters, including the window size of the texture feature. The suitable window size should be tuned according to the spatial resolution of an image and the characteristics of the objects in the image.

However, a disadvantage of high-order texture measure is that it requires more complicated and intensive computation. For a large hyperspectral data set, it will take much more computing resources and time to accomplish the analysis.

6. Conclusion

The traditional GLCM texture is calculated based on a mono-spectral image. In this study, we propose a novel VGLCM texture feature based on hyperspectral images. The motivation of this study is to more effectively represent the texture information from hyperspectral images.
The experiments based on: the ACC achieved by the VGLCM are satisfactory. To address the issue that same objects may show different spectral characteristics based on the attributes of hyperspectral data set, this paper takes hyperspectral image as a pseudo data cube to extract the features. Then we extend traditional 2D-GLCM to a 3D-GLCM form. The use of all the pixels contained in the image in different spectral bands is very interests in the classification task, but it cause many problems like taking much more computing resources and time to accomplish the analysis. Indeed, in future work, we will be interested in some solution to optimize the different parameters related to building the 3D-GLCM (moving directions, texture window..).

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