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Classifying Hyperspectral Imageries

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Abstract: Classification is the process of assigning a pixel to the class to which it belongs. Classification may be supervised or unsupervised. This paper summarizes various classification methodology used in satellite imaging. Paper aims at providing information regarding various classification processes existing now days in remote sensing. Hyperspectral data set (AVIRIS (Moffet field, 1992)) has been used to verify accuracy of the classification algorithms. The results are displayed in the form of confusion matrix and Kappa coefficient. Experiments are performed on ENVI 4.5. The overall aim of this paper is to assess the relative performance of five approaches to classification in remote sensing maximum likelihood, neural network, minimum distance, parallelepiped and support vector machine. Also various factors involved in their performance are examined in detail.

Index Terms: Hyperspectral, ENVI, Classification

I. INTRODUCTION

A number of methodologies have been proposed for remote sensing data. These methodologies can be classified as supervised and unsupervised classification. Remote sensing data used for classification may also be categorized as panchromatic, multispectral or hyperspectral image. These imagery are differentiated on the basis of number of bands in the image. Panchromatic image are single band image and are generated by adding all the light reflected by object in visible spectrum (400 nm to 700 nm). Multispectral imagery contains a few bands up to 20 or 30. These bands contain information in discrete intervals [1]. A portion of infrared radiation is covered in this imaginary. Hyperspectral image contains more than 100 bands. These images are captured in a contiguous spectrum but narrow bandwidth (10 nm).

The science of remote sensing consists of interpretation of measurements of electromagnetic energy reflected from or emitted from a target. Sensors mounted on aircraft or satellite platforms record this electromagnetic radiation [2]."The main advantage of satellite remote sensing over alternative forms of environmental data gathering is that large global surface areas can be monitored without the need for ground level surveys [3]. In addition, satellite observations are less costly than aerial surveys for long term and large area mapping and monitoring".

Remote sensing satellites record data in digital form, which is then processed by computer. Computer processing applications range from calibration of the data for the effects of factors such as the changing response of sensors over time to the identification of patterns in multi- and hyper-spectral data that relate to features on the ground [6].

Image classification involves the execution of several stages. Moreover, within each of these principal stages there are several sub stages and hence further decisions need to be made. Interrelationship between number of features, sample size and classifier complexity are the factors responsible for performance of a classifier. One of the important stages in image classification is that of collection of samples for training and testing the classifier. Sample size has an influence on the classification accuracy with which estimates of statistical parameters are obtained for statistical classifiers [4][5]. Sample selection also depends on a number of factors which finally affect classification accuracy. The factors affecting sample selection are:

A. Number of training sites for sample collection.
B. Sampling method (random or systematic sampling).
C. Data source for labeling training sites (ground data, air photographs etc).
D. Timing of data collection.

With high-dimensional data sets, such as those acquired by an imaging spectrometer, the training set size requirements for the correct application of a classification system may be too high. It is well known that the probability of misclassification of a decision rule does not increase as the number of features increases, as long as number of training samples is arbitrarily large. However, it has been observed in practice that additional features may degrade the performance of a classifier if the number of training samples that are used to design the classifier is small relative to the number of features (peaking phenomenon). [5][7][8][9] Study the effect of sample size and sampling plan in detail.

II. LAND COVER CLASSIFICATION

Typically the steps involved in land cover classification are feature extraction, training and labeling.

A. Feature extraction maps high dimensional data in to lower dimension without degrading its physical properties using a transformation function. Feature extraction perform the following two task
B. Separates useful information from raw data or noise.
C. Reduce dimensionality to enhance the efficiency of classifier.
D. Training process can be supervised or unsupervised. Ground truth data is used to train classifier for classification process.
E. Labeling allocates the individual pixel to their most likely class. This is the final step of a classification process. Pixel allocating to class can follow any of the various algorithms available.

III. CLASSIFICATION TECHNIQUES

A. Maximum likelihood

The most commonly used statistical classification methodology is based on maximum likelihood, a pixel-based probabilistic classification method which assumes that spectral classes can be described by a normal probability distribution in multispectral space. This traditional approach to classification is found to have some limitations in resolving interclass confusion if the data used are not normally distributed [13]. As a result, in recent years, and following advances in computer technology, alternative classification strategies have been proposed [14].

B. Neural network

Artificial neural networks (ANN) have been used in remote sensing over the past decade, mainly for image classification. Studies carried out using ANN suggest that, due to their nonparametric nature, they generally perform better than statistical classifiers. The performance of a neural network classifier depends to a significant extent on how well it has been trained. During the training phase, the neural network learns about regularities present in the training data and, based on these regularities, constructs rules that can be extended to the unknown data. However, the user must determine a number of properties such as the architecture of network, learning rate, number of iterations and learning algorithms, all of which affect classification accuracy. There is no clear rule to fix the values of these parameters, and only rules of thumb exist to guide users in their choice of network parameters [15].

C. Support vector machine

Recently, a new classification technique based on statistical learning theory, called support vector machines, has been applied to the problem of image classification [2][3][8]. Support vector machines use optimization algorithms to find the optimal boundaries between classes, and generalize these boundaries to unseen samples with the least errors among all possible boundaries separating the classes and minimizing confusion between classes.

D. Minimum distance

Minimum distance classifier is based on mean vectors. It is one of the simplest kinds of classification scheme. It calculates the Euclidian distance from the mean vector of each class to each unknown (unclassified) pixel[16][17]. Based on selected criteria (standard deviation or threshold) some pixel may be unclassified if they do not fulfill the criteria. Otherwise all pixels are classified to nearest class [10] [18].

IV. RESULT AND DISCUSSION

Result of classification depends upon following factors.

A. *Class separability*
B. Training sample size
C. Dimensionality

D. Classifier type Classification improves if.

1) Class parameter values are chosen more precisely.

2) Class separability increases.

3) The ratio of training size to dimensionality increases.

4) More accurate classifier is chosen.

Table 1 to table 4 shows the performance of maximum likelihood, minimum distance, neural network, and support vector machine with different number of bands. Minimum number of training pixel must be greater than number of bands. Experiments show that accuracy of SVM is not affected by number of bands. Also it has been found that with increase in number of training pixel classification accuracy increases. SVM is not affected by Hughes phenomenon [3]. Other classifiers are affected by Hughes phenomenon it can be seen that classification accuracy decreases with increase in number of bands. A total of six classes were used for classification. Principal component analysis was performed for feature extraction.

Table 1 Classification accuracy with 120 pixels per class

Classifier	Number of bands								
	5	10	20	30	40	50	60	80	100
Support Vector Machine	93.6	93.4	94	93.4	92.3	92.1	91.5	90.5	89.3
Maximum Likelihood	91.12	89.3	88.9	88.7	88.8	85.9	84.3	80.8	80.1
Neural Network	88.4	89.6	89.4	89.4	88.5	88.7	85.6	83.3	79.6
Minimum Distance	89.5	90.30	91.4	89.4	87.20	86.20	84.30	82.88	80.21

Table 2 Classification accuracy with 200 pixels per class

Classifier	Number of bands								
	5	10	20	30	40	50	60	80	100
Support Vector Machine	95.8	95.4	95	98.8	93.2	92.9	92.5	91.5	90.3
Maximum Likelihood	92.2	90.3	89.9	89.7	89.8	87.9	86.3	85.8	84.1
Neural Network	90.6	89.7	89.4	88.4	88.3	87.7	87.5	86.5	85.6
Minimum Distance	90.8	90.6	91.2	90.2	89.20	88.20	87.50	86.88	85.21

Table 3 Classification accuracy with 300 pixels per class

Classifier	Number of bands								
	5	10	20	30	40	50	60	80	100
Support Vector Machine	96.8	95.8	95.2	94.8	93.2	92.6	91.2	91	90.2
Maximum Likelihood	93.8	92.6	91.6	91.2	90.8	89.6	89.2	88.8	88.1
Neural Network	90.4	89.8	88.2	88	87.8	87.5	86.6	86.3	85.6
Minimum Distance	90.5	90.20	92.4	88.8	87.60	86	85.80	85.2	84.2

Table 4 Classification accuracy with 500 pixels per class

Classifier	Number of bands								
	5	10	20	30	40	50	60	80	100
Support Vector Machine	97.3	96.8	95.4	94.4	93.8	92.6	92.4	91.8	90.8
Maximum Likelihood	95.8	94.3	92.5	91.8	90.6	90.4	89.8	89.6	88.8
Neural Network	91.2	90.8	90.6	89.8	88.5	88.2	87.2	86.3	86.1
Minimum Distance	90.8	90.6	92.4	91.4	89.80	89.40	89.20	88	87.8

V. CONCLUSION

From experiment it is clear that SVM is unaffected by dimensionality of feature space. SVM depend on the margin with which data is separated not on the number of features. SVM has been found as the best classifier for hyperspectral data. Performance of Maximum likelihood is highly affected by number of training pixel. Study concludes that even at high dimensionality with large number of training pixel better accuracy can be achieved

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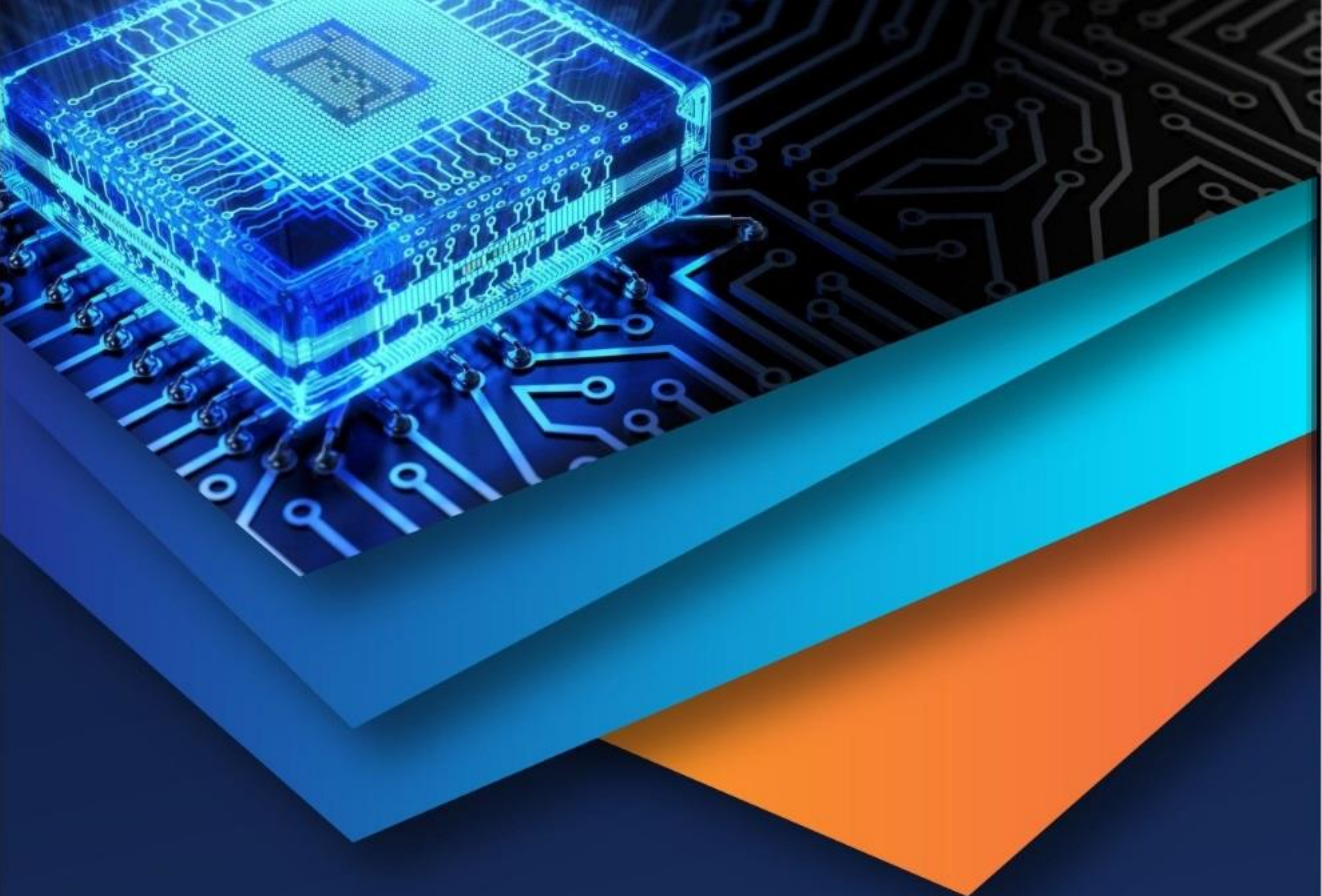

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