AN ASSESSMENT ON THE PERFORMANCE OF SUPPORT VECTOR MACHINE OVER TRADITIONAL PARAMETRIC AND NON-PARAMETRIC TECHNIQUES FOR SATELLITE IMAGE CLASSIFICATION

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ABSTRACT: Land cover is one of the crucial elements for scientific research and real life earth science applications. For many years the recognition of the land cover has been used as the fundamental variables in several fields such as agriculture, environment, forestry, geology, hydrology and oceanography. Remote sensing data has been the prolific source of land cover information, due to its large coverage over the earth surface. Classification of surface features in satellite imagery is one of the utmost important applications of remote sensing. Classification of remote sensing images may be grouped into parametric and non-parametric techniques. For parametric classifier such as the Maximum Likelihood Classifier (MLC), the data are assumed to follow statistical distribution to estimate accurate parameters, which are highly related to the selection of appropriate training class. Existing datasets of multispectral remote sensing images were used in evaluating each of the classifier methods. In the study, we are comparing the performance of the parametric and non-parametric classifiers such as Maximum Likelihood Classifier (MLC), Minimum Distance Classifier (MDC), and Parallelepiped classifier with an artificial intelligence method - the Support Vector Machine (SVM) for land cover pattern recognition and analyse the performance of each method in classification or recognition of the features in terms of efficiency. Efficiency is assessed by evaluating accuracy and statistical differences in several scenes. The results from the use of the Support Vector Machine (SVM) and other techniques are compared and evaluated.

1. INTRODUCTION

Supervised classification is one of the most commonly undertaken analyses of remotely sensed data. The output of a supervised classification is effectively a thematic map that provides a snapshot representation of the spatial distribution of a particular theme of interest such as land cover. Thematic maps are crucial to many applications, as well as, for example, the basis for techniques to study land cover changes or the information required to parameterize many environmental models (Foody and Mathur, 2004).

New methods had been developed to deal with ever complex and challenging environment, which include methods based on artificial intelligence these methods might be the key towards better and more accurate mapping of our environment, but their use is still at its infancy due to the lack of understanding on their performance. Classification of remote sensing images may be grouped into parametric and non-parametric techniques (Atkinson and Tatnall, 1997). For parametric classifier such as the maximum likelihood classifier (MLC), the data are assumed to follow statistical distribution to estimate accurate parameters, which are highly related to the selection of appropriate training class.

Another classification algorithm, the decision tree, has been used successfully for a wide range of classification problems including remote sensing image classification. Decision tree based techniques have substantial advantages for remote sensing classification problems because of their flexibility, non-parametric nature, and ability to handle non-linear relations between features and classes (Pal and Mather, 2003). As with any classification algorithm, the accuracy of a classification produced by a decision tree is dependent on a number of factors, such as the size and composition of the training data set, the attribute selection method, the choice of pruning method, and the type of decision tree classifier employed. In the past few years, the Support Vector Machine (SVM) or a machine learning algorithm has been proposed to overcome classification problem with the use of other classifiers (Pal and Mather, 2004).

2. MATERIALS AND METHOD

2.1 The Study Area

Kuala Rompin is situated in the east coast of Peninsular Malaysia, under the Pahang state administration. The geographical coordinates of the study area are 2° 49’ N, 103° 29' E. The main economic activities in Kuala Rompin are fisheries, agriculture, eco-tourism and government service sectors. The area is mainly covered by a small township area, mangroves, agricultural lands and beaches (Figure 1). Kuala Rompin is one of the gateways to the magnificent Tioman Island in Pahang.

2.2 The Data

The Systeme Probatoire pour l`Observation de la Terre (SPOT) 5 satellite imagery of Kuala Rompin was acquired on 20 July 2006 and topography map with 1:50 000 scale and ground truth data were used as a basis for image classification. The image was obtained from Malaysian Remote Sensing Agency (ARSM) with radiometric and atmospheric corrections to level 1B. The image was geometrically corrected and registered to WGS 84 datum and UTM Zone 47 projection. The digital image processing and classification was performed using the ENVI 4.3 image processing and analysis software. Prior to performing the classification and accuracy assessment of the image, a ground truth covering Kuala Rompin area was carried out in June 2007.

Figure 1: The SPOT 5 image of the study area.

The ground truth process will help on determining the number of object class for the accuracy assessment training area. The GPS geo-positioning unit was used to record the location of the area identified as well as visual verification of the area. The ground truthing was performed around the area using a Garmin GPSMap and the collected data were transferred to the computer for processing using the proprietary software of Garmin, the MapSource. The remote sensing data and the coordinates were overlaid to check the correctness of both data.

2.3 Image Classification

Supervised classifications may be considered to comprise three distinct stages: training, allocation and testing. Quantitative descriptions of each class to be mapped are derived in the training stage. For this, areas of known class membership, training sites, are identified in the image and their remotely sensed response characterised from the sample of pixels they contain. The quantitative descriptions, training statistics, derived from the training stage are used in association with the selected classification decision rule to allocate each pixel in the image to the class with which it has greatest similarity in the class allocation stage of the analysis. In the final stage of a supervised classification, the accuracy of the thematic classification derived is assessed (Foody and Mathur, 2004).

The region of interest (ROI) or the training area for image classification as shown in Figure 2 was selected according to the visual interpretation and ground truth data. The ground truthing is one of the best techniques to acquire a good ROI selection. The separability of each ROI classes were calculated using the Jeffries-Matusita and Transformed Divergence separability measures to obtain the information on how well the separability among each object class. Most of the object class have values of 2.0 portray that it was highly separable, pairwise of sand - built-up, forest - non-forest and sand-cleared land were least separable with the average value of 1.5. Six object were grouped in the ROI based on the ground truth campaign; Water, Forest Vegetation, Non – Forest Vegetation, Cleared Land, Sand and Built-Up.

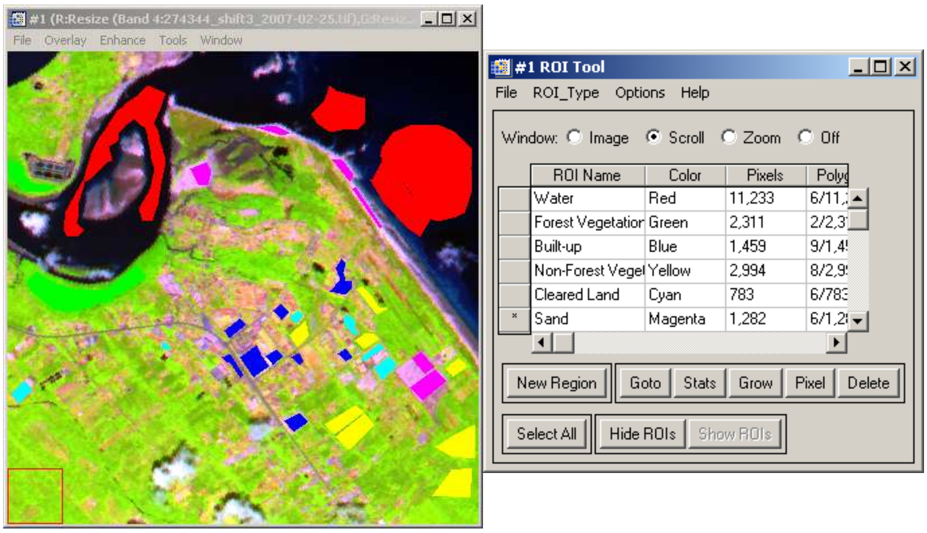


Figure 2: Ground truth data

3. RESULTS AND DISCUSSION

3.1 Support Vector Machine

The Support Vector Machine (SVM) provides a training approach of the pixels based on the neighboring of the separating hyperplanes which is called the support pixel vectors (Richards and Jia, 2006). Supervised classification on the image using a support vector machine (SVM) to identify the class associated with each pixel. SVM provides good classification results from complex and noisy data because SVM was derived from statistical learning theory. It separates the classes with a decision surface that maximizes the margin between the classes. The classifications were done to several SVM Kernels namely the Linear, Polynomial, Radial Basis Function and Sigmoid to test the accuracy of each Kernel type with default settings. Figure 3 shows the SVM classification results.

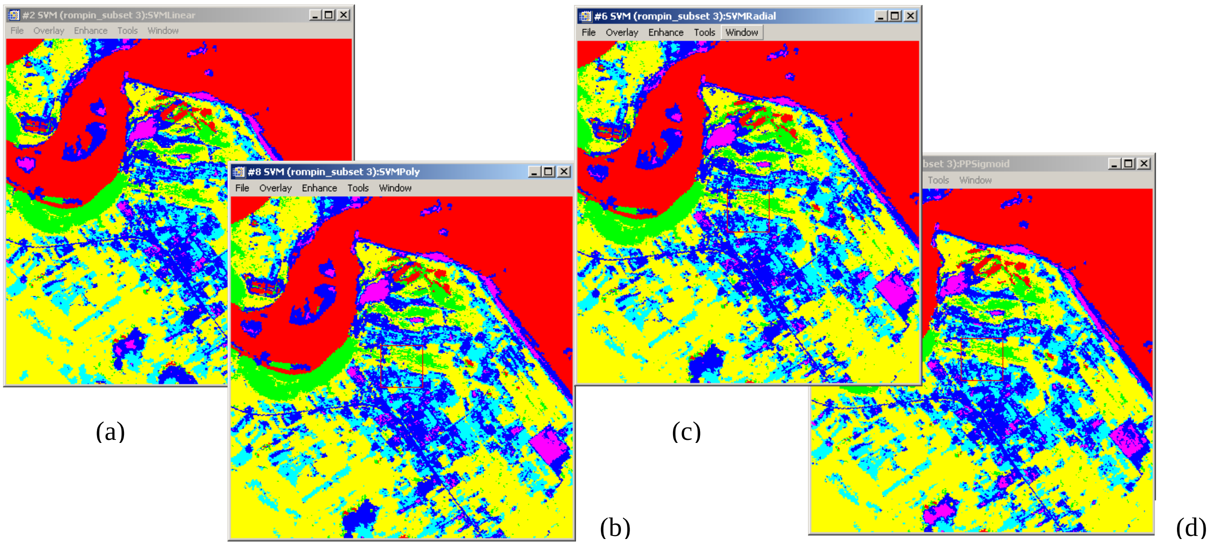


Figure 3: Classification results based on Support Vector Machine with (a) Linear (b) Polynomial (c) Radial Basis Function and (d) Sigmoid Kernels

3.2 Maximum Likelihood

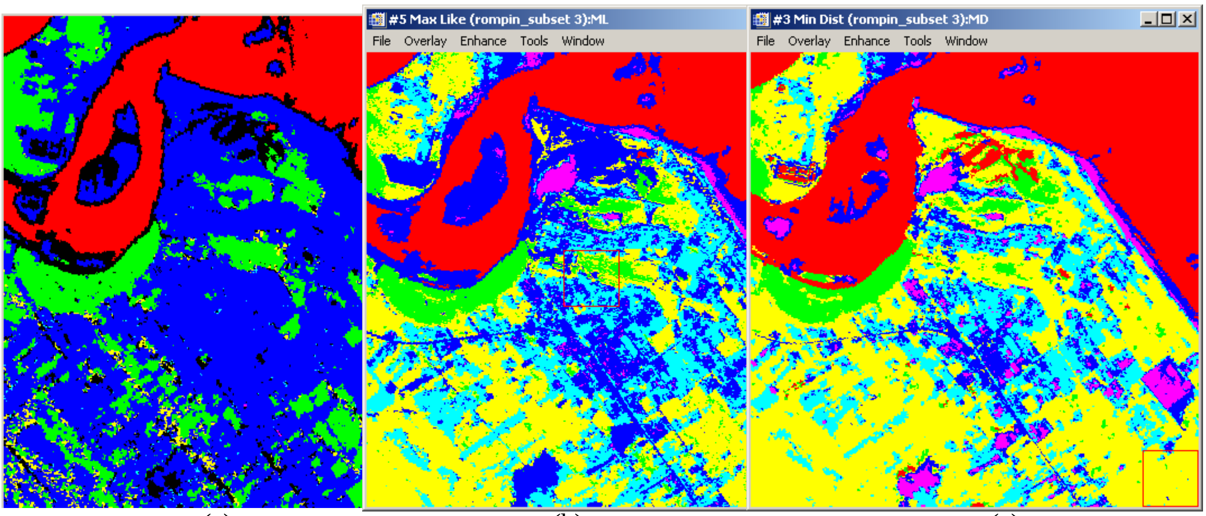
Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability of likelihood. The maximum likelihood classifier (MLC) is based on the assumption that the members of each class are normally distributed in feature space. MLC is based on the probabilistic methods, whereby each pixel is computed based on the probability to be assigned to a given class rather than another (Girard and Girard, 2003), this end up to classifying pixels in a selective manner of belong to or does not belong to the classes.

3.3 Minimum Distance

The minimum distance classification (MD) depends on the accurate estimation of the mean vector and the covariance matrix foe each spectral class (Richards and Jia, 2006) which are selected through the ROI. In this view, it is crucial to have a sufficient number of training pixels for each of the object classes. Inaccurate estimates of the elements of covariance matrix will lead to a poor classification (Richards and Jia, 2006). The minimum distance technique uses the mean vectors of each end member and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. All pixels are classified to the nearest class according to its spectral properties.

3.4 Parallelepiped

The parallelepiped classifier is a simple supervised classifier operated by inspecting histogram of the individual spectra components of the available training data (Richards and Jia, 2006). Parellelpiped classification is based on radiometric model but not on measurement or distance or probability and every pixel is situated in an n-dimensional hyperspace (Girard and Girard, 2003). The dimensions of the parallelepiped classification are defined based upon a standard deviation threshold from the mean of each selected class. Although it is in principle a simple classifier, there is drawback of this technique, which there can be gaps between the parallelepipeds and pixels in those regions will not be classified (Richard and Jia, 2006) therefore the pixels are designated as unclassified. Figure 4 shows the results from the use of the three classifiers.



(a) (b) (c)

Figure 4: Classified image of the study area using (a) Parallelepiped classifier
(b) Maximum Likelihood classifier and (c) Minimum Distance classifier

3.5 Accuracy Assessment

The result of an accuracy assessment is highly related to the training pixel associated with it. In this assessment, the training classes were carefully selected to a homogeneous pixel for highly accurate training pixels. The results of SVM with several kernels were compared to ML, MD, and PP was presented in the above graph. The most highly accurate technique was SVM: Kernel Radial (95.87%), followed by SVM: Kernel Polynomial (95.67), ML (95.63), and SVM: Kernel Sigmoid (94.61), MD (93.95%) and PP (73.48%). Table 1 and Figure 5 summarize the comparison in terns of performance of the different classifiers. The Kappa Coefficient statistics allow further assessment of classification accuracy with higher value indicates better result.

Table 1: Accuracy assessment results and Kappa Coefficient of the image classification

Classification Technique	Overall Accuracy	Kappa Coefficient
SVM Kernel : Radial	95.87%	0.9355
SVM Kernel : Polynomial	95.67%	0.9324
Maximum Likelihood	95.63%	0.9319
SVM Kernel : Linear	95.43%	0.9286
SVM Kernel : Sigmoid	94.61%	0.9158
Minimum Distance	93.95%	0.9055
Parallelepiped	73.48%	0.5952

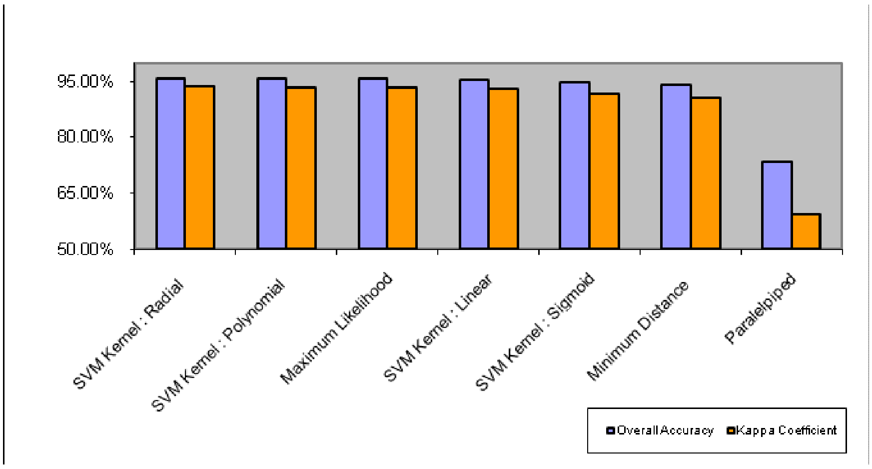


Figure 5: Results of the accuracy assessments of the seven classification techniques.

4. CONCLUSION

The result shows that overall six classifiers show a high accuracy rate of more than 90%. Two SVM classifications namely SVM: Polynomial and SVM: Kernel Radial produce a higher accuracy compared to that ML and MD but generally all the classification results is good with accuracy more than 90% except for the PP classification with 73.48%. The reason of low accuracy produced by the Parallelepiped classifier as compared the other classifiers is the gaps between the parallelepiped are considered as undesignated class. The dimensions of the parallelepiped classification are defined based upon a standard deviation threshold from the mean of each selected class. The correlated data in parallelepiped can cause overlaps of the parallelepiped since their sides are parallel to the spectral axes (Richards and Jia, 2006), thus some data failed to be separated. The accuracy assessment typically provides us with an overall accuracy of the map to be produced and the accuracy for each class in the map. This is the primary reason why the accuracy assessment for classification of satellite imageries often carried out before any mapping projects.

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