

IMAGE CLASSIFICATION ON EX-MINING LAND AREA USING ECHO CLASSIFIER

by

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ABSTRAK

Aktiviti-aktiviti perlombongan bijih timah di Malaysia semenjak tahun 1930an lagi telah mengakibatkan pemasaalahan kepada struktur tanah dan proses degradasi di kawasan tanah bekas lombong. Tetapi kawasan ini mempunyai potensi dan permintaan yang tinggi untuk dibangunkan bagi tujuan kawasan perumahan, industri, taman rekreasi, penanaman semula hutan dan juga sebagai bahan input untuk pembangunan industri pembinaan dan bahan pengisian.

Tujuan penyelidikan ini adalah untuk mengklasifikasikan bentuk permukaan kawasan tanah bekas lombong yang luas dan sangat kompleks dengan menggunakan kaedah teknologi kawalan jauh ('remote sensing'). Kaedah ini telah terbukti berguna untuk mengetahui bentuk permukaan sesuatu kawasan serta menjimatkan masa dan lebih murah berbanding dengan kaedah penyiasatan yang sebenar di sesuatu kawasan kajian. Penyelidikan ini juga termasuk membuat penilaian keatas beberapa algoritma pengklasifikasi imej, penghasilan peta bentuk permukaan kawasan tanah bekas lombong daripada imej satelite serta pengumpulan maklumat-maklumat kawasan kajian untuk membuat analisa kuantitatif dan juga penilaian ketepatan ke atas kaedah-kaedah yang digunakan didalam penyelidikan ini.

Pengklasifikasi ('classifier') seperti 'Clustering (ISODATA)', 'Minimum Euclidean Distance', 'Maximum Likelihood' dan 'ECHO' digunakan untuk mengklasifikasikan imej satelite. Hasil penyelidikan didapati bahawa pelbagai pengklasifikasi memberi hasil yang berbeza apabila mengklasifikasi imej di kawasan kajian terutama bila digabungkan dengan lain-lain set data. Keputusan ujian daripada

analisa kualitatif mendapati bahawa pengklasifikasi 'ECHO' memberikan hasil klasifikasi yang hampir-hampir tepat dan berkebolehan untuk memproses pelbagai skil set-set data. Hasil penyelidikan dengan menggunakan 'ECHO' ke atas kawasan tanah bekas lombong ditunjukkan di dalam tesis ini dan fokus untuk kajian masa hadapan adalah untuk memperbaiki kejituan data dengan penggunaan set-set data tambahan dan penyelidikan didalam membangunkan algoritma yang lebih stabil kegunaannya.

ABSTRACT

Tin Mining activities in Malaysia since the 1930s have caused a major problem to the soil structure and degradation process in the ex-mining land areas. But these areas have great potential and highly demand to develop especially on housing, industrial, recreational, agroforestry and also valuable feed material for industrial development such as construction and filling material.

The purpose of this study is to map the landcover of a large and complex surface of an ex-mining land area using remote sensing technology. Remote sensing imagery has proven useful to generate landcover and it is timely, potentially less expensive than conventional ground methods. Study goals included evaluation of various classification algorithms, deriving a landcover map of the ex-mining land using satellite image and collection of ground truth points in order to perform a more quantitative analysis and accuracy assessment of the methods used.

Clustering (ISODATA), Minimum Euclidean Distance, Maximum Likelihood and ECHO classifier are used for satellite image classification. Research results confirmed that different classifiers perform differently when classifying the study area especially when the merged dataset was used. Qualitative analysis of the results shows that the ECHO classifier provides the clearest, most accurate classification and superior in handling multiple scale datasets. Results from the ECHO classification on the ex-mining land area are presented in this thesis and future development will focus on

improving accuracy by adding additional data sets and conducted a research for development of classifiers to produce more stable algorithms.

Keywords :

Image classification, pattern recognition, satellite remote sensing, classifiers, ex-mining land, tin tailings, ECHO classifier, accuracy assessment.

CHAPTER 1: INTRODUCTION

1.1 Introduction

Image Processing and Classification involves the manipulation of images to extract information, emphasize or de-emphasize certain aspects of the information contained in an image and/or perform statistical or other analyses to extract non-image information. Although certain image processing and classification procedures are frequently used, there is no definitive “standard” set of processing steps because each project requires individual attention. Some processing decisions may simply be a matter of personal preference and the quality of data varies greatly.

Advances in sensor technology for Earth observation make it possible to collect multispectral data. Such multispectral data will have several impacts on processing methods such as more classes will possibly classify and more power will be needed to process. Classification of a remote sensing image involves pattern recognition, which is defined as the science –and –the art- of finding meaningful patterns in data. It is difficult to identify more than a few patterns with the human eye and it does not involve any scientific reasoning. In human visual image interpretation, the criteria used for classification can be broadly defined by the tone or colour, size, shape, shadow, pattern, texture, and spatial relationships of the ground targets. An interpreter’s knowledge, experience, and familiarity with a study area also contribute to the classification

process. However, with the help of a computer system, pattern recognition can be done in a scientific manner.

Many image processing and analysis techniques have been developed to aid the interpretation of remote sensing images and to extract as much information as possible from the images. The choice of specific techniques or algorithms to use depends on the goals of each individual project. In the real world, there are many applications where a classifier that can recognize on a single class of samples is sufficient. The maximum likelihood (ML) classifier, one of the most widely used relative classifiers, is not a good choice here since the relative comparison of log-likelihood values requires training samples for, or otherwise defining all other classes (i.e., fully supervised) is an onerous shortcoming especially when there are large number of classes and/or features to deal with. The necessary number of training samples is dependent on the number of features and the number of classes, and insufficient training samples compared to the number of features can degrade the classification performance.

Research has shown that classification multispectral image often is significantly improved using combination of different techniques (Maniere et al. 1984). This thesis will focus on classifying the multispectral data using combination of unsupervised and supervised methods for classification. The classifier is known as Extraction and Classification of Homogeneous Objects (ECHO) classifier and it is prove to be a good classifier for classifying the ex-mining land area. The classified image is then compared to the geographical data that are assured to be true. The classification process is not complete until the accuracy of classification is assessed. Other than the skill of the user,

the accuracy of classification is dependent upon the methods and capabilities of the tools used.

1.2 Objective of Research

It is the objective of this research to better understand the characteristics of the multispectral data relative to the analysis process, and to select classifiers which increase the feasibility of its use. Although most analysis and classification of data are conducted by machine, sometimes it is useful and necessary for human to interpret and analyze data.

This research also focuses on feature identification over a large area such as the ex-mining land in Kinta Valley through a comparison of several different methods. The best methods will be proposed to solve problem on image classification using multispectral data on the ex-mining land. The intent is to present quantitative methods in such a way that it will be useful for others who wish to use remotely sensed data and for investors that are interested in developing the ex-mining land by using the thematic map produce from this research. The landcover map on ex-mining land is important because the ex-mining land has good potential to develop for many purposes and the land is cheap.

1.3 Problem Statement

Mining activities since the 1930s have resulted in about 113,700 hectares of tin tailings throughout Peninsular Malaysia, or about 2% of total land area (Plate 1.1). The early economic development of Malaysia was directly related to the tin mining industry. The revenue from the tin was used for the building of roads and railways reinvestment into the local economic activities. Mining activities stimulated the development of new towns and urban centres in the country. Among the areas that have outgrown their origins in the tin industry to become large urban centres are Kuala Lumpur and Ipoh. Since the collapse of the tin market in 1985, tin mining in Malaysia has become less significant industry than in past years (Rafek 1985). As a result, large areas of ex-mining land are now left derelict. These areas have great potential for many types of land use development.

The ex-mining land consists of water body (14.4%) and tin tailings (85.6%). Perak has the highest tin tailings (60,500 hectares) followed by Selangor/Kuala Lumpur (24,750 hectares) and Johore (5,140 hectares). Only 4,730 hectares (4.2%) of the ex-mining land had been utilised for agriculture and others (5.5%). Hence, large tracts of tin tailings remain unproductive. Among the important information on tin tailings areas are data on soil characteristics. Generally, there is no systematic soil survey of tin mining land in the country. The exact distribution and the different types of tailings are not known. Much of the information required for planning reclamation is likely to be available from the Department of Mineral and Geosciences Malaysia. The information consists of mining records and mining scheme plans. The mining records contain detailed information about the history of mining activities where it can be related to the

mining scheme plans. Mining scheme plans are normally produced at a scale of 1:6336. These data are quite complex with the existence of many overlapping mining schemes and the changes in mining scheme boundaries from time to time.



Plate 1.1: Tin mining activities often involve degradation of tropical forests and making the soil properties and water table level adverse for reforestation

Tin tailings are the waste products of tin mining, resulting from gravel pumping and dredging methods, the two commonly practiced mining methods in the country. The mining operations involve removing ore deposits from the ground using running water. As a result, an irregular landform comprising of a mixture of large barren sand mounds, gravel piles and slime interspersed with large ponds were developed, as shown in Plate 1.2 and 1.3. This landscape is popularly known as a lunar landscape. Due to different mining methods and deposition procedures employed, tin tailings show a wide range of physical and chemical characteristics (Lim et al., 1981). Ex-mining land is

usually characterised by poor ground conditions and a very irregular profile of the bedrock.



Plate 1.2: Sand tailings from gravel pumping



Plate 1.3: Slime retention area and water pond

Figure 1.1 shows the gravel pump mining process. As the result of the mining activities, a complex tin tailing as shown in Figure 1.2 is produced. The soils lack systematic variations and consequently they cannot be surveyed easily (Radzali et al., 1993).

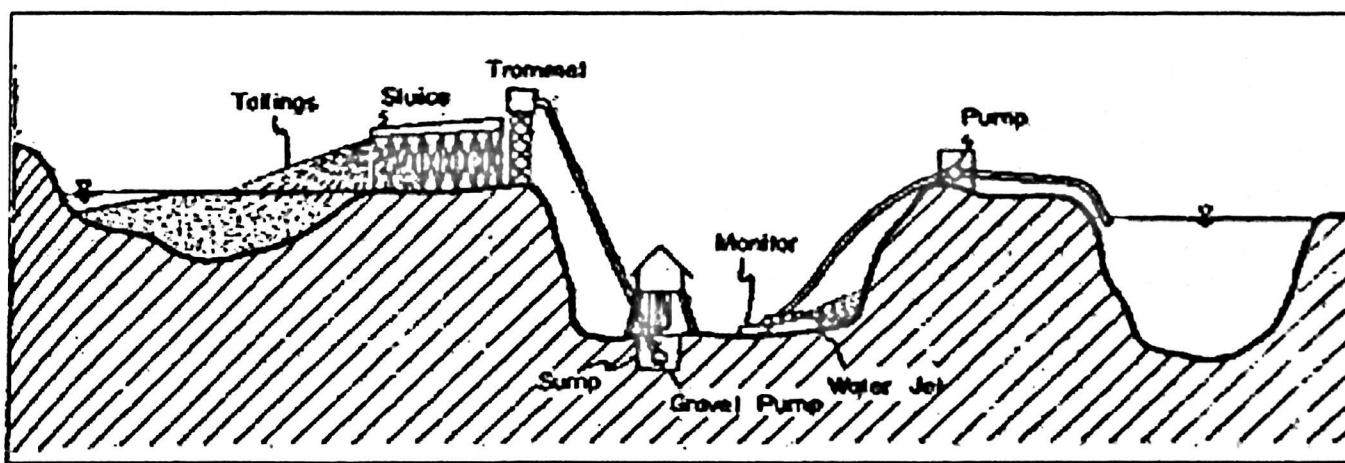


Figure 1.1: Gravel pump mining method (after JICA, 1981)

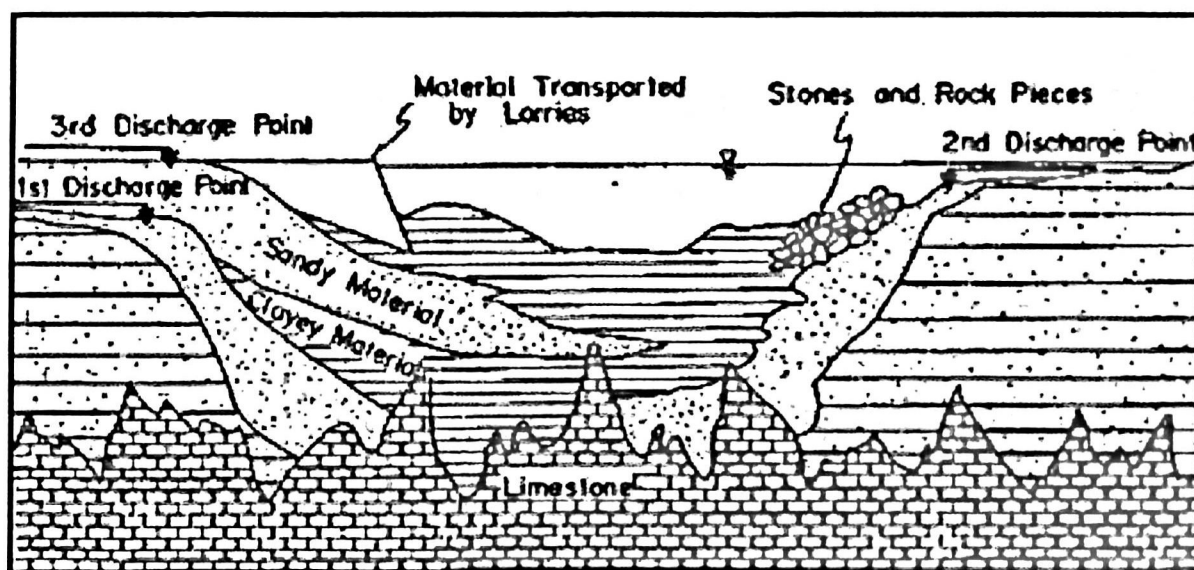


Figure 1.2: A profile of tin tailings (after JICA, 1981)

The loss of nutrient content during the mining process and a high soil surface temperature is also major problems, especially for agricultural use. Due to the highly disturbed nature of the soil structure and the degradation process, the soil on ex-mining

land has reduced engineering strength properties. Thus, any development for industry and housing would face foundation-engineering problems.

Even though there are many constraints on the future use of ex-mining land, there are still demands to develop this land. Among the reasons for the high demand is the low cost of acquiring the land. As the land is flat, it is easy to build access roads and drainage systems. The other factor to be considered is their location, which is generally near to cities.

The study of the ex-mining land reclamation dates back to the 1930's. Most studies of ex-mining land relate to agricultural uses, housing, industrial and recreational areas. Some studies such as for housing and industrial purposes are emphasized on subsurface ground conditions, especially from the viewpoint of foundation engineering. This includes financial and economic studies. Unfortunately, the identification of subsurface ground conditions based on detailed geotechnical investigations, including drilling work and laboratory testing, as proposed by JICA is very costly.

1.4 Proposed Solution

The studies of soil types in ex-mining land are useful because some of the tin tailings materials are valuable for industrial development. Referring to Figure 1.3, tailing materials are highly valuable for use in industry and construction, and as filling material. Based on these facts, Mineral Research Centre is involved in many research activities using tin tailings as feed materials to produce products for the Mineral

Industry. Other potential usage of an ex-mining land is for afforestation, agroforestry, housing, industrial and recreational area. Some examples are shown in Plate 1.4, 1.5, 1.6 and 1.7.

As mentioned above, the detailed soils investigation using geotechnical methods and other soil testing is very costly. Attempts to use aerial photographs for extraction of ground features are not encouraging as the ground conditions of ex-mining land are heterogeneous and complex. A major problem occurs during the accuracy assessment when getting the aerial imagery into the same projection as the Landsat image. In many cases, the pixels were counted as misclassified when they were only out of place by one pixel width, likely less than the error introduced by geo-rectification of the aerial photographs. In order to solve a number of problems in soils investigation in ex-mining land, we suggest the usage of remote sensing technology, which might be suitable for this study.



Plate 1.4 **Palm Oil Plantation on the ex-mining land**

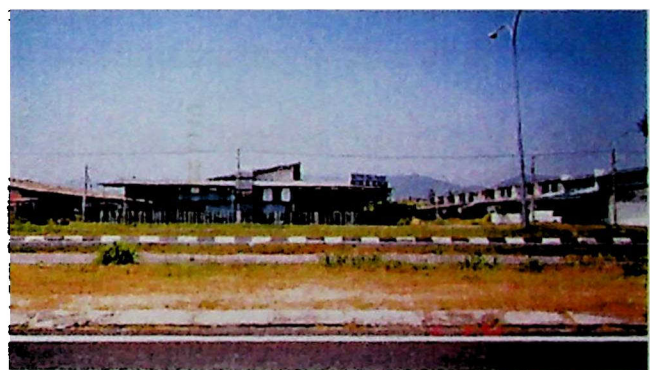


Plate 1.5 **Industrial area that are developed on the ex-mining land**



Plate 1.6 Houses development on the ex-mining land

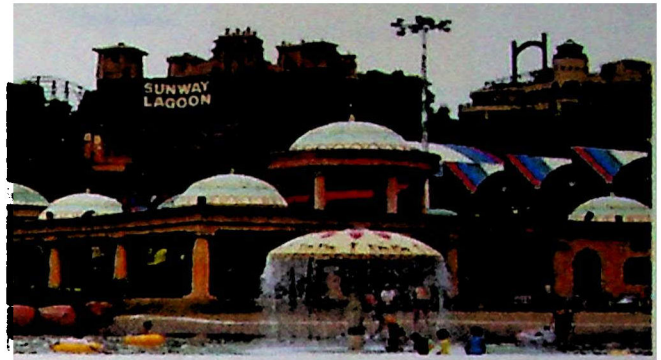


Plate 1.7 A famous recreational place that develop from the ex-mining land

Satellite remote sensing is one of the most effective methods for monitoring land cover or land use study. The data from satellite remote sensing has proved that it can be extremely useful for gathering many types of information, but is still strongly under utilized. Remote sensing technology is capable of deriving important features from a complex ground surface on ex-mining land and cost effective. Few studies have conducted using remote sensing technique for classification the surface of an ex-mining land. We will investigate the reason for it and propose a method that is cost effective, fast processing and good classification with less error when classifying the surface area of an ex-mining land based on accuracy assessment formulas.

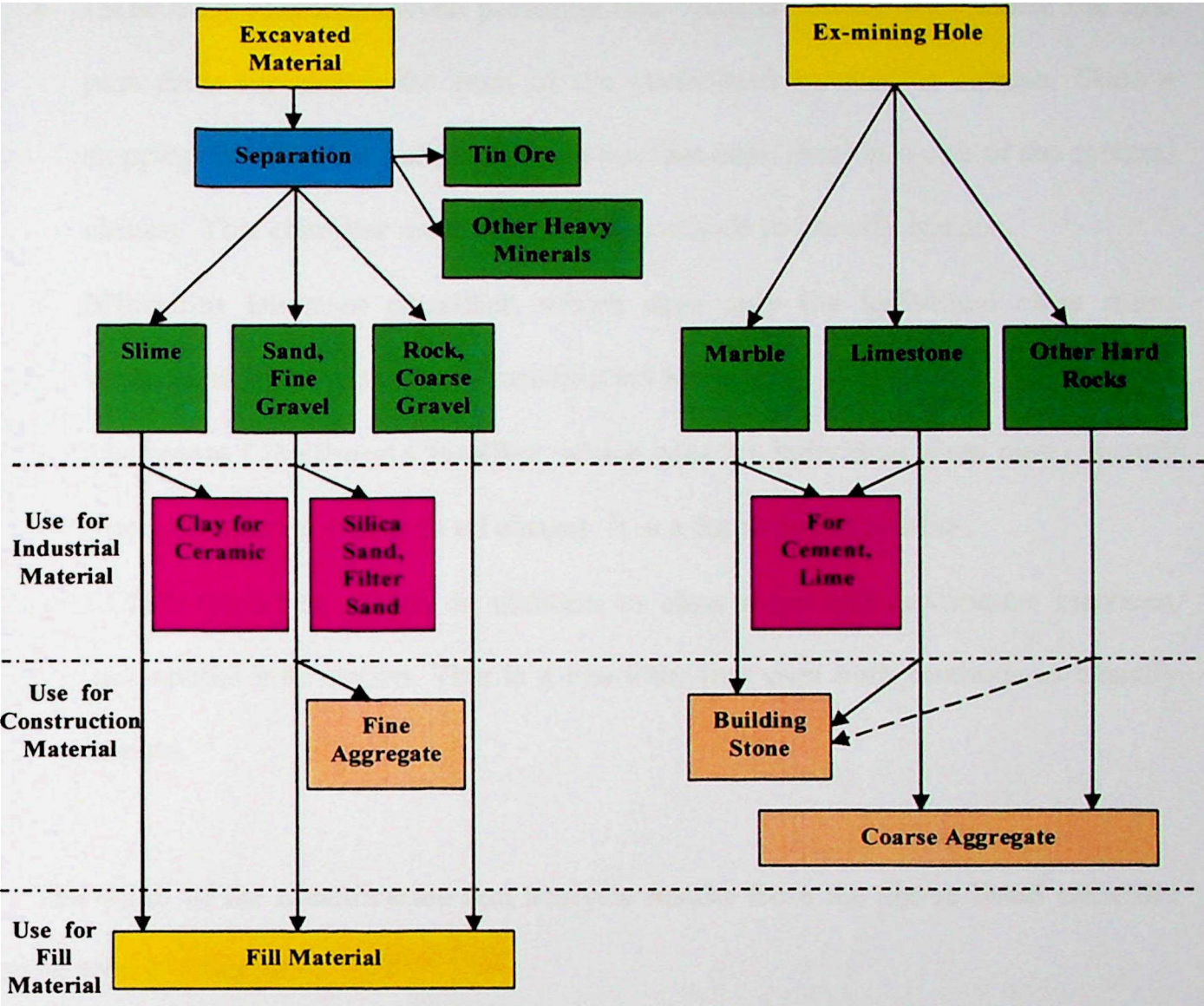


Figure 1.3: Use of tin mining by product (after JICA, 1981)

We use image from Landsat TM on Kinta Valley in Ipoh as an input data for classification and use the classifier below to classified, compare and evaluate the classification process. The classifiers to be use in this research are:

- **ISODATA classifier** which performs two “passes” on the data where the first pass finds the means for each of the predefined number of classes. Once a stopping criterion has met, pass two classifies each pixel into one of the spectral classes. This classifier use unsupervised methods to classify images.
- **Minimum Distance classifier**, which uses only the individual class mean vectors and it use supervised classification methods.
- **Maximum Likelihood Classifier**, which uses the individual class mean vectors plus a covariance matrix to all classes. It is a supervised classifier.
- **ECHO classifier**, which, in addition to class mean and covariance matrices, uses spatial information. This is a classifier that uses both methods to classify images.

The detail of the classification and analysis results from the above listed classifier can be seen in Chapter 4.

1.5 Contributions

The information that was extract from this research are important especially for land developing, mineral industries feed material, landcover/landuse mapping especially on change detection and for developing a spatial decision support system on the ex-mining land for Malaysian environment.

The thesis also shows that the remote sensing technology can generate meaningful and useful information from a complex ground surface on the ex-mining

land. This technology is cost effective and fast processing time during classification compared to the actual geotechnical investigations. Generally, the best performance occurs in the case of ECHO classifier that uses combination of unsupervised and supervised classification procedures when classifying the ex-mining land. The ECHO classifier performs good classification although limited number of training samples is used.

1.6 Organization of the Thesis

The organization of this thesis is as follows. Chapter 2 presents a formal statement of the remote sensing classification methods with a brief review of previous works. The important of accuracy assessment in producing an accurate thematic map also is explain in this chapter.

In Chapter 3 discusses the selected classifier for the image classification and analysis. The theory about the ECHO classifier and its algorithm is explains in this chapter.

Experimental results with real LANDSAT Thematic Mapper data of the study area are presented with discussion in Chapter 4. Finally, conclusion and suggestions for future research in Chapter 5 complete this thesis.

CHAPTER 2 – TOWARDS AN EFFECTIVE METHOD FOR MULTISPECTRAL IMAGE CLASSIFICATION

2.1 Introduction

A human analyst attempting to classify features in an image uses the elements of visual interpretation to identify homogeneous groups of pixels which represent various features or land cover classes of interest. Digital image classification uses the spectral information represented by the digital numbers in one or more spectral bands, and attempts to classify each pixel based on this spectral information. This type of classification is termed spectral pattern recognition. In either case, the objective is to assign all pixels in the image to particular classes or themes (e.g. water, forest, urban area, etc.). The resulting classified image is comprised of a mosaic of pixels, each of which belong to a particular theme, and is essentially a thematic “map” of the original image.

When talking about classes, we need to distinguish between information classes and spectral classes. Information classes are those categories of interest that the analyst is actually trying to identify in the imagery, such as different kinds of vegetation, different geologic units or rock types, etc. Spectral classes are groups of pixels that are uniform (or near-similar) with respect to their brightness values in the different spectral channels of the data. The objective is to match the spectral classes in the data to the information classes of interest. Rarely is there a simple one-to-one match between these

two types of classes. Rather, unique spectral classes may appear which do not necessarily correspond to any information class of particular use or interest to the analyst. Alternatively, a broad information class may contain a number of spectral subclasses with unique spectral variations. Using the forest as example, spectral subclasses may be due to variations in age, species, and density, or perhaps as a result of shadowing or variations in scene illumination. It is the analyst's job to decide on the utility of the different spectral classes and their correspondence to useful information classes.

Common classification procedures can be broken down into two broad subdivisions based on the method used: supervised classification and unsupervised classification. In a supervised classification, the analyst identifies in the imagery homogeneous representative samples of the different surface cover types (information classes) of interest. These samples are referred to as training areas. The selection of appropriate training areas is based on the analyst's familiarity with the geographical area and their knowledge of the actual surface cover types present in the image. Thus, the analyst is "supervising" the categorization of a set of specific classes. The numerical information in all spectral bands for the pixels comprising these areas are used to "train" the computer to recognize spectrally similar areas for each class. The computer uses a special program or algorithm of which there are several variations, to determine the numerical "signatures" for each training class. Once the computer has determined the signatures for each class, each pixel in the image is compared to these signatures and labeled as the class it most closely "resembles" digitally. Thus, in supervised classification we are first identifying the information classes which are then used to determine the spectral classes which represent them.

Unsupervised classification in essence reverses the supervised classification process. Spectral classes are grouped first, based solely on the numerical information in the data, and then matched by the analyst to information classes if possible. Programs, called clustering algorithms, are used to determine the natural statistical groupings or structures in the data. Usually, the analyst specifies how many groups or clusters are to be looked for in the data. In addition to specifying the desired number of classes, the analyst may also specify parameters related to the separation distance among the clusters and the variation within each cluster. The final result of this iterative clustering process may result in some clusters that the analyst will want to subsequently combine, or clusters that should be broken to down further - each of these requiring a further application of the clustering algorithm. Thus, unsupervised classification is not completely without human intervention. However, it does not start with a pre-determined set of classes as in a supervised classification

2.2 Classification Methods

The image classification process offers a variety of classification methods as well as tools to aid in the analysis of the classification results. Most classification methods use some measure of the distance between points in the spectral space to assess the similarity of spectral patterns. Cells that are close together in spectral space have similar spectral properties and have a high likelihood of imaging the same surface features.

Classifier is designed for the use with conventional multispectral imagery in the classification process. The functional form of a classifier determines the shape of the decisions boundaries that it can produce. More complex classifiers can create even more complex boundaries. Obviously, the more complex the classifier, the more powerful it is in terms of its ability to discriminate among various classes of different shapes. The process of designing a classifier are divided into two: supervised learning classifier that uses training samples from the classes on interest and unsupervised learning classifier which uses unlabeled samples. More detailed background and related works on both types of classifier design will be discussed below.

2.2.1 Unsupervised Learning Classifier

The unsupervised learning paradigm has no external teacher to oversee the training process, and the system forms “natural grouping” of the input pattern. The advantage of this paradigm is that “Natural” is always defined explicitly or implicitly in the clustering system itself. In other words, the finally achieved results with unsupervised learning reflect the input data itself more objectively. The disadvantage of unsupervised learning is that the finally achieved objective classes are not necessary to have subjective meanings. The question have is how do we know if the algorithm already separates the feature space fine enough and put the classification boundaries at the right places? This is a hard problem that always shadows unsupervised learning. It makes unsupervised learning techniques not as powerful as some of us expected. We will discuss below the ISODATA Clustering classifier, one of the unsupervised learning classifier that will be use for the purpose of this research.

(a) ISODATA Classifier

The Iterative Self-Organizing Data Analysis Techniques (ISODATA) clustering algorithm is a widely used clustering method to partition the image data in the multispectral space into a number of spectral classes (Jensen, 1996). This type of clustering algorithms, however, suffers from several limitations. One of the limitations is that ISODATA requires the user to specify the number of clusters beforehand. The second limitation is that it requires the user to specify the starting positions of these clusters through an educated guess. The clustering starts with a set of arbitrarily selected pixels as cluster centers with exception no two may be the same (Swain, 1978). The choice of the initial locations of the cluster centers is not critical, but it will evidently affect the time it takes to reach a final, acceptable result (Richards, 1993). It does not matter where the initial cluster centers are located, as long as enough number of iterations is allowed (ERDAS, 1997). Because no guidance is available in general, a logical procedure is adopted in LARSYS (Richards, 1993). The initial cluster centers are chosen evenly distributed along the diagonal axis in the multidimensional feature space. This is a line from the origin to the point corresponding to the maximum digital number in each spectral component. Other similar procedures used in ISODATA have been proposed in Jensen (1996) and ERDAS (1997). However, few studies have investigated the problem for the past years about how random choice of the initial cluster centers and those procedures proposed by ERDAS (1997) and Jensen (1996) may affect final classification results. The study thus will examine this very important but apparently neglected problem.

The third limitation associated with ISODATA is its processing speed. ISODATA is computationally intensive when processing large data sets since, at each iterative step, all pixels in the whole data set must be checked against every cluster center. Furthermore, this method tends to suffer from performance degradation as the number of bands, the number of pixels, or the number of clusters increases (Richards, 1993; Viovy, 2000).

2.2.2 Supervised Learning Classifier

The supervised learning paradigm employs a teacher in the machine learning process (S.Haykin, 1999). The advantage of this paradigm is that all separate classes in the algorithms are meaningful to humans. The disadvantage of this paradigm is that all objective data samples are forced into subjective meaningful classes without considering if these samples are objectively separable or not.

Supervised learning sometimes also meets difficulties in collecting labeled data. For example, a multi-sensory robot may acquire input data at a very fast speed. It may acquire a new utterance in seconds; it may also acquire a huge amount of shape and color information in milliseconds. If we ask a human teacher to label all the data a robot requires, the work is very labor intensive and tedious. In our real life, not everything can be clearly labeled. These difficulties limit the applications of supervised learning to some extent. In short, supervised learning is limited in many aspects. Blindly using the supervised learning technique is just like fitting our feet into unknown

shoes. It is very hard to guarantee a fit. The following sections provide a description of some supervised learning classifiers that are relate to this research.

(a) Minimum Distance (to means) Classifier

This decision rule is considered to be the simplest one. The distance between the candidate pixel, the pixel to be classified, and the mean of the classes defined, is considered. The pixel is assigned to the class, which has the closest mean. The minimum distance is based on the equation for Euclidean distance (Swain and Davis, 1978):

$$SD_{xyc} = \sqrt{\sum_{i=1}^n (\mu_{ci} - X_{xyi})^2} \quad (2.1)$$

where:

n	=	number of bands (dimensions)
i	=	a particular band
c	=	a particular class
X_{xyi}	=	data value of pixel x,y in band i
μ_{ci}	=	mean of data values in band i for the sample for class c
SD_{xyc}	=	spectral distance from pixel x,y to the mean of class c

The only parameter used to decide the class for the candidate pixel is the mean and other important parameters, such as covariance and correlation. Misclassification is likely if there are big differences in the variance of the classes and if the candidate pixel is closer to the mean of the low variance class. The decision boundary in feature space will be linear and located equidistant

between the class means and orthogonal to a line joining their means (See Figure 2.1).

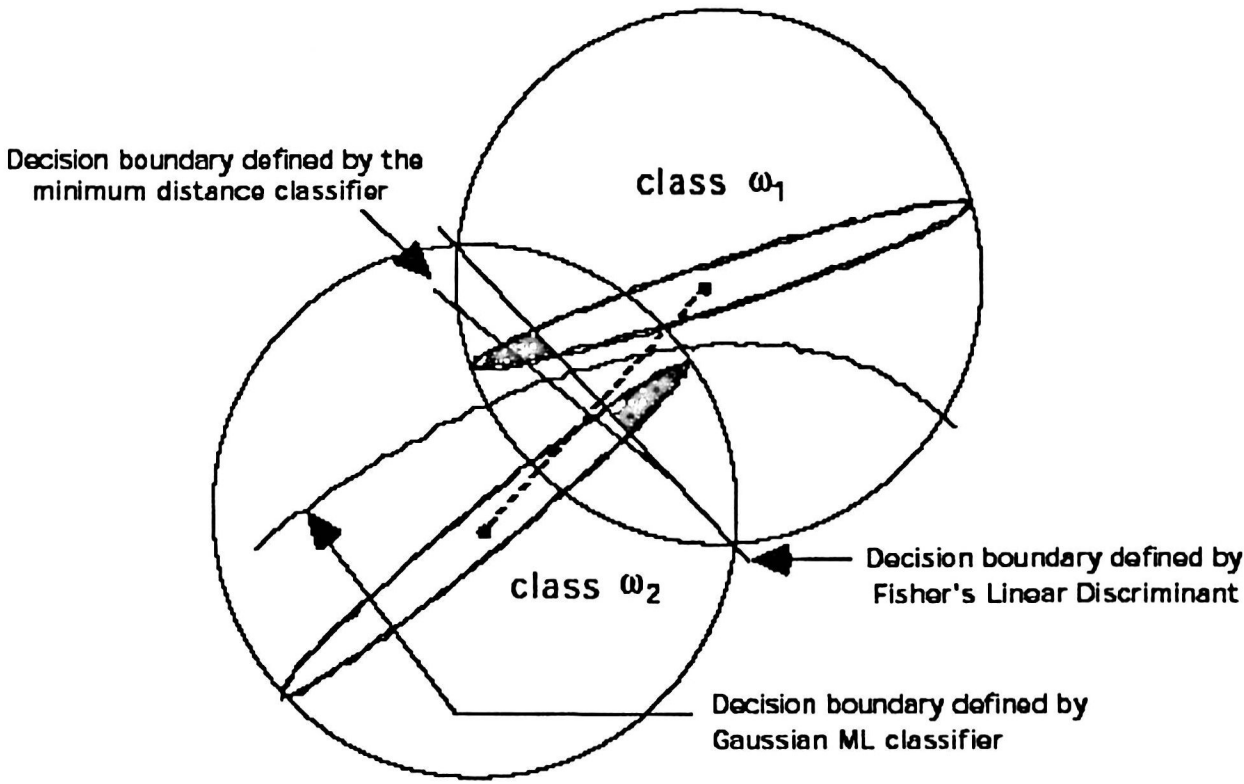


Figure 2.1 Examples of sources of classification error for the minimum distance classifier

A drawback of the Minimum Distance approach is that it fails for small n data vectors, because the density estimate becomes degenerate.

(b) Mahalanobis Distance Classifier.

Mahalanobis Distance was introduced by P.C. Mahalanobis in 1936. In Mahalanobis Distance, a distance measure is based on correlations between the

variables and by which different patterns could be identified and analyzed with respect to base or reference point (Taguchi & Juguhum, 2002)

Mahalanobis is a very useful way of determining the “similarity” of a set of values from an “unknown”: samples to a set of values measured from a collection of “known” samples. It is superior to Euclidean Distance because it takes distribution of the points (correlations) into account.

This method also assumes a normal distribution of the band histograms. In addition to the mean value of the signature class the covariance matrix (covariance and variance) is included in the calculation, which tends to over classify signatures with relatively large values in the covariance matrix.

$$D = (X - M_c^T)(cov_c^{-1})(X - M_c) \quad (2.2)$$

where:

D	=	Mahalanobis distance
c	=	a particular class
X	=	the measurement vector of a candidate pixel
M_c	=	the mean vector of the signature of class c
cov_c	=	the covariance matrix of the pixels in the signature of class c
		cov ⁻¹
T	=	transposition function

(c) Fisher's Linear Discriminant

Fisher's linear discriminant (Fisher, 1936) is very popular among users of discriminant analysis. Some of the reasons for this are its simplicity and unnecessary of strict assumption. However it has optimality properties only if the underlying distributions of the groups are multivariate normal. It is also easy to verify that the discriminant rule obtained can be very harmed by only a small number of outlying observations. Outliers are very hard to detect in multivariate data sets and even when they are detected simply discarding them is not the most efficient way of handling the situations.

$$g_i(\mathbf{X}) = (\mathbf{X} - \boldsymbol{\mu}_i)^T \mathbf{S}^{-1} (\mathbf{X} - \boldsymbol{\mu}_i) \quad (2.3)$$

choose class i if $g_i(\mathbf{X}) \leq g_j(\mathbf{X})$ for all $j = 1, 2, \dots, m$.

In this case, the classes are assumed to have a common covariance specified by $\mathbf{S}$. This is equivalent to assuming the classes do not have the same variance in all features, the features are not necessarily uncorrelated, but both classes have the same variance and correlation structure. The decision boundary in feature space will be linear, but its location between the class mean values will depend upon $\mathbf{S}$.

(d) Maximum Likelihood/Bayesian Classifier

This method requires a normal distribution of the bands included in the classification and is based on the probability that a pixel belongs to a particular class. The maximum likelihood equation assumes that the probabilities for all the classes are equal. If the class probabilities are known it is possible to include these by using the Bayesian classifier. In the same way as the Mahalanobis classifier, this method also tends to over-classify signatures with large values in the covariance matrix.

$$D = \ln(a_c) - [0.5 \ln(|\text{cov}_c|)] - [0.5(\mathbf{X} - \mathbf{M}_c)^T(\text{cov}_c^{-1})(\mathbf{X} - \mathbf{M}_c)] \quad (2.4)$$

where:

- D** = weighted distance (likelihood)
- c** = a particular class
- X** = the measurement vector of the candidate pixel
- a_c** = percent probability that any candidate pixel is a member of class c (defaults to 1.0, or is entered from a priori knowledge)
- cov_c** = the covariance matrix of the pixel in the sample of class c
- $|\text{cov}_c|$** = determinant of Cov_c (matrix algebra)
- $\ln$** = natural logarithm function
- T** = transposition function (matrix algebra)
- $\mathbf{M}_c$** = the mean vector of the signature of class c