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Comparative Study On Hyperspectral Remote Sensing Images Classification Approaches

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Abstract- Hyperspectral remote sensing image is also known as an "Imaging Spectrometry" emerged as a promising technology for detection and identification of minerals, terrestrial vegetation, man-made materials and backgrounds. The word "Hyperspectral" is used to distinguish sensors with many tens or hundreds of bands from the more traditional multiple sensors. The success of a hyperspectral remote sensing image classification technique depends on many factors. The availability of high-quality remotely sensed imagery and ancillary data, the design of a proper classification procedure, and the analyst's skills and experiences are the most important ones. For a particular study, it is often difficult to identify the best classifier due to the lack of a guideline for selection and the availability of suitable classification algorithms in hand. Comparative studies of different classifiers are thus frequently conducted. Therefore, in this paper we compared several classification approaches with its factors.

Index terms - Remote Sensing (RS), Maximum Likelihood Classifier (MLC), Digital Orthophoto Quadrangle (DOQ), Iterative Self-Organizing Data Analysis (ISODATA), Digital Number (DN).

1. INTRODUCTION

Hyperspectral imaging is concerned with the measurement, analysis, and interpretation of spectra acquired from a given scene (or specific object) at a short, medium or long distance by an airborne or satellite sensor [1]. The information contained in hyperspectral images allows the characterization, identification, and classification of the land-covers with improved accuracy and robustness. However, several critical problems should be considered in the classification of hyperspectral data, among which: (i) the high number of spectral channels, (ii) the spatial variability of the spectral signature, (iii) the high cost of true sample labeling, and (iv) the quality of data. In particular, the high number of spectral channels and low number of labeled training samples create the problem of the curse of dimensionality [2] and, as a consequence, result in the risk of over fitting the training data. There are many factors affecting the hyperspectral data quality, ranging from the external factors such as an atmospheric condition to the internal factors like sensor noise, sensor transfer characteristics, and material spectrum. For a specific object or material, the noise-dominated bands will certainly deteriorate the discrimination capability, and hence degrade the classification performance. On the other hand, the spectral difference among materials also varies across bands [3]. Classification is a challenging but important task for hyperspectral remote sensing applications, including land use analysis, pollution monitoring, wide-area reconnaissance, and field surveillance [4]. This paper provides the major steps in remote sensing classification and approaches with comparison.

2. REMOTE SENSING CLASSIFICATION PROCESS

Major steps in remote sensing classification are selection of remotely sensed data, selection of a classification system and training samples, image preprocessing, feature extraction and selection, selection of suitable classification method, post-classification processing and evaluation of classification performance. These steps are depicted in figure 1.

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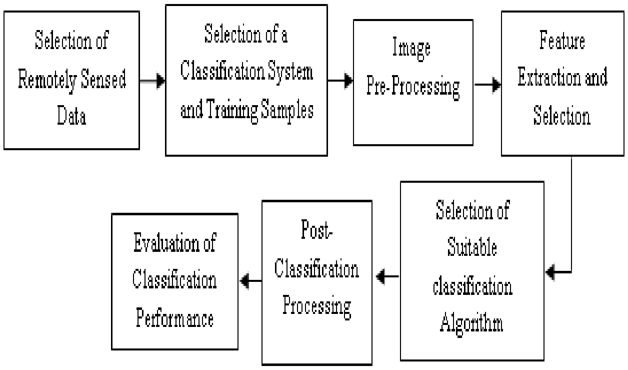

Figure 1: Steps in Remote Sensing Classification

2.1 SELECTION OF REMOTELY SENSED DATA

Remotely sensed data have different spatial, radiometric, spectral, and temporal resolutions. Understanding the strengths and weaknesses of different types of sensor data is essential for selecting suitable remotely sensed data for image classification. Some previous literature has reviewed the characteristics of major types of remote sensing data [5]. The selection of suitable remotely sensed data requires considering factors such as the needs of the end user, the scale and characteristics of the study area, available image data and their characteristics, cost and time constraints, and the analyst's experience in using the selected images. Atmospheric condition is another important factor that influences the selection of remote sensing data. Monetary cost is often an important factor affecting the selection of remotely sensed data.

2.2 SELECTION OF A CLASSIFICATION SYSTEM AND TRAINING SAMPLES

A suitable classification system is a prerequisite for successful classification. Generally, a classification system is designed based on the user's needs, the spatial resolution of the remotely sensed data, compatibility with previous work, available image-processing and classification algorithms, and time constraints. Such a system should be informative, exhaustive, and separable [6]. In many cases, a hierarchical classification system is adopted to take different conditions into an account. A sufficient number of training samples and their representativeness are critical for image classifications [7]. Therefore, selection of training samples must consider the spatial resolution of the remote sensing data being used, the availability of ground reference data, and the complexity of the landscapes under investigation.

2.3 IMAGE PRE-PROCESSING

Image preprocessing may include the examination of image quality, geometric rectification, and radiometric and atmospheric calibration. If different ancillary data are used, the data conversions among different sources or formats and quality evaluation of these data are necessary before they can be incorporated into a classification procedure.

The examination of original images to see on any remote sensing system–induced radiometric errors is necessary before the data are used for further processing. Accurate geometric rectification or image registration of remotely sensed data is a prerequisite for combining different source data in a classification process.

If a single-date image is used for classification, atmospheric correction may not be required [8]. However, when multitemporal or multisensor data are used, atmospheric calibration is mandatory [9]. Topographic correction is important if the study area is located in rugged or mountainous regions [10].

2.4 FEATURE EXTRACTION AND SELECTION

Selecting suitable variables is a critical step for successfully performing an image classification. Many potential variables may be used in image classification; it includes spectral signatures, vegetation indices, transformed images, textural or contextual information, multitemporal images, multisensor images, and ancillary data.

Because of the different capabilities of these variables in land-cover separability, the use of too many variables in a classification procedure may decrease classification accuracy [11]. It is important to select only those variables that are most useful in separating land-cover or vegetation classes, especially when hyperspectral or multisource data are employed.

2.5 SELECTION OF A SUITABLE CLASSIFICATION ALGORITHM

In recent years, many advanced classification approaches, such as artificial neural networks, decision trees, fuzzy sets, and expert systems, have been widely applied in image classification. [12] discussed the status and research priorities of land-cover mapping for large areas [13] assessed land-cover classification approaches with medium spatial resolution remotely sensed data. Published works by [14] specifically focused on image-processing approaches and classification algorithms. In general, image classification approaches can be grouped into different categories, such as supervised versus unsupervised, parametric versus nonparametric, hard versus soft (fuzzy) classification, per-pixel, sub pixel, and per field [15]. For the sake of convenience, [15] grouped classification approaches as perpixel, sub pixel, per-field, contextual, and knowledge-based approaches, and a combination approach of multiple classifiers.

In practice, many factors, such as the spatial resolution of the remotely sensed data, different data sources, classification systems, and the availability of classification software, must be taken into account when selecting a classification method for use.

2.6 POST CLASSIFICATION PROCESSING

Post classification processing is an important step in improving the quality of classifications [16]. Its roles include, the recoding of land use/cover classes, removal of "salt-and-pepper" effects, and modification of the classified image using ancillary data or expert knowledge. Traditional per-pixel classifiers based on spectral signatures often lead to salt-and-pepper effects in classification maps due to the complexity of the landscape.

Thus, a majority filter is often applied to reduce noise. Also, ancillary data are often used to modify the classification image based on established expert rules. Data describing terrain characteristics can be used to modify classification results based on the knowledge of specific vegetation classes and topographic factors. In urban areas, housing or population density is related to urban land-use distribution patterns, and such data can be used to correct some classification confusions between commercial and high-intensity residential areas or between recreational grass and crops [17].

2.7 EVALUATION OF CLASSIFICATION PERFORMANCE

The evaluation of classification results is an important process in the classification procedure. Different approaches may be employed, ranging from a qualitative evaluation based on expert knowledge to a quantitative accuracy assessment based on sampling strategies. A classification accuracy assessment generally includes three basic components: (1) sampling design, (2) response design, and (3) estimation and analysis procedures [18]. The error matrix approach is one of the most widely used in accuracy assessment [19]. In order to properly generate an error matrix, one must consider the following factors: reference data collection, classification scheme, sampling scheme, spatial autocorrelation, and sample size and sample unit [20].

After the generation of an error matrix, other important accuracy assessment elements, such as overall accuracy, omission error, commission error, and kappa coefficient, can be derived [19-24].

3. CLASSIFICATION APPROACHES

Image classification is an important part of the remote sensing, image analysis and pattern recognition.

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In some instances, the classification itself may be the object of the analysis. The image classification therefore forms an important tool for examination of the digital images. Classification is a method of grouping data into classes based on some specific similarity of characteristics.

The classification scheme and the method of classification to be used are primarily dependent upon the application of the classification [25]. At present, there are different image classification procedures used for different purposes by various researchers, they are categorized according to training samples, parameters, pixels, output and spatial information.

3.1 According to training samples

3.1.1 Supervised classification

In supervised classification, the image data are classified into a fixed number of predetermined information classes selected by the analyst. This is accomplished by the following procedure. Training areas closely representing the desired information classes are selected within the image area. Statistical information of the spectral pattern of the information classes is generated from these training classes. This statistical information serves as the reference data during the classification stage. In this stage, each pixel is assigned into one of the information classes based on some predetermined classification strategy. Some of the commonly used classification strategies are minimum distance to means, parallel piped classifier, and maximum likelihood classifier (MLC) [26].

3.1.2 UNSUPERVISED CLASSIFICATION

Unsupervised classification is a method of partitioning the image into clusters based on the spectral properties of the pixels. An analyst provides the number of desired clusters and all the image pixels are partitioned into the specified number of clusters. After the image is partitioned into clusters, each and every cluster is then assigned to a specific information class by using some form of reference data such as an aerial photograph or Digital Orthophoto Quadrangle (DOQ).

The two most commonly used algorithms for unsupervised classification are k-means and Iterative Self-Organizing Data Analysis Technique (ISODATA) [25].

	Supervised classification	Unsupervised classification
Knowledge	First apply knowledge then classify.	First classify and then apply knowledge.
Errors	Creating more opportunity for the operator to make errors.	Creating less opportunity for the operator to make errors.
Unique Classes	Allow unique classes to go unrecognized.	Allows unique classes to be recognized as distinct-units.
Information	Define useful information categories and examine their spectral separability.	Determine spectral classes and define their informational utility.
Spectral Data	We impose our perceptions on the spectral data.	Spectral data imposes constraints on our interpretation.

Table 1: Comparison of Supervised and Unsupervised Classification

3.2 According to parameters

3.2.1 Parametric classifiers

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The parameters (e.g. mean vector and covariance matrix) are often generated from training samples. When landscape is complex, parametric classifiers often produce

'noisy' results. Another major drawback is that it is difficult to integrate ancillary data spatial and contextual attributes and non-statistical information into a classification procedure. These classifiers rely on assumptions of data distribution. The performance of a parametric classifier depends mostly on how well the data match with pre-

defined models and on the accuracy of the estimation of the

model parameters. Traditionally most classifiers have been grounded to a significant degree in statistical decision theory. They suffer from the Hughes phenomenon (i.e. curse of dimensionality) and consequently it might be difficult to have a significant number of training pixels. They are not adequate to integrate ancillary data (due to difficulties on classifying data at different measurement scales and units) [27].

3.2.2 Non-parametric classifiers

In non-parametric classifier, no assumption about the data is required. Non-parametric classifiers do not employ statistical parameters to calculate class separation and are especially suitable for incorporation of non-remote-sensing data into a classification procedure. A nonparametric classifier uses a set of nonparametric signatures to assign pixels to a class based on their location, either inside or outside the area in the feature space image. A nonparametric signature is based on an AOI that you define in the feature space image for the image file being classified [27].

	Parametric Classification	Non-parametric Classification
Training Samples	The parameters (e.g. mean vector and covariance matrix) are often generated from training samples.	Does not take into account the distribution of the training samples.
Properties of data	It depends on properties of the data.	It does not depend on properties of the data.
Statistical Parameters	Grounded to a significant degree in statistical decision theory.	Do not employ statistical parameters to calculate class separation

Table 2: Comparison of Parametric and Non-Parametric Classification

3.3 According to pixels

3.3.1 Per-pixel classifier

Per-pixel classification pattern analyses per-pixel spectrum characteristics, and categorizes each pixel into a certain class by statistical methods (such as discriminant function, clustering) [28], which was brought forth in the early 1970s and is a rather mature technique. Traditional per-pixel classifiers typically develop a signature by combining the spectra of all training-set pixels for a given feature. The resulting signature contains the contributions of all materials present in the training pixels, but ignores the impact of the mixed pixels. Per-pixel classification algorithms can be parametric or non-parametric [29].

3.3.2 Sub pixel classifier

Most classification approaches are based on per-pixel information, in which each pixel is classified into one category and the land-cover classes are mutually exclusive. The presence of mixed pixels has been recognized as a major problem, affecting the effective use of remotely sensed data in per-pixel classifications [30].

Subpixel classification approaches have been developed to provide a more appropriate representation

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and accurate area estimation of land covers than per-pixel approaches, especially when coarse spatial resolution data are used. The spectral value of each pixel is assumed to be a linear or non-linear combination of defined pure materials (or end members) [31].

3.3.3 Object-oriented classifier

Object-oriented classification pattern deals with image objects, which share the similar attributes, such as Digital Number (DN) value, spectral characteristics, texture, size, shape, compactness, context information with adjacent image objects, etc. [32]. The image objects can be extracted through RS image segmentation technique (to put similar characteristic & spatial conjoint pixels into a same image object). Object-oriented classification pattern uses the image objects as the basic processing units, calculates per-object's characters, and extracts land-cover information from RS imagery.

	Pixel-based classification	Object-oriented classification
Information	Uses information from individual pixels.	Uses shape information to describe patterns.
Examination	Examine imagery on a pixel by pixel basis.	Move towards viewing objects made up of pixels.
Usage	Uses mainly DN values and ancillary data in its class assignment.	Uses DN values, objects, ancillary data fuzzy systems, expert knowledge and the hierarchical relationships.
Pixilation	Pixilated with a salt and peppered look.	Pixilation is eliminated resulting in a more real world output.
Homogeneous Objects	Does not allow for the creation of homogenous objects.	Treat homogeneous objects as entities rather than pixels.

Table 3: Comparison of Pixel-Based and Object-oriented Classification

3.3.4 Per-field classifier

The per-field classifier is designed to deal with the problem of environmental heterogeneity, and has shown to be effective for improving classification accuracy. The per-field classifier averages out the noise by using land parcels (called 'fields') as individual units. GIS plays an important role in per-field classification, integrating raster and vector data in a classification. The vector data are often used to subdivide an image into parcels and classification is based on the parcels, avoiding the spectral variation inherent in the same class [33].

3.4 According to output

3.4.1 Hard classification

Hard classification is used for making a definitive decision about the land cover class that each pixel is allocated to a single class. The area estimation by hard classification may produce large errors, especially from coarse spatial resolution data due to the mixed pixel problem. Supervised and unsupervised classification algorithms typically use hard classification logic to produce a classification map that consists of hard, discrete categories (e.g., forest, agriculture). The distinguishing characteristic of hard classifiers is that they all make a definitive decision about the landcover class to which any pixel belongs [34].

3.4.2 Soft (fuzzy) classification

Soft classification provides more information and potentially a more accurate result, for coarse spatial resolution data classification. Fuzzy set classification logic takes into account the heterogeneous and imprecise nature (mix pixels) of the real world. Proportion of the m classes within a pixel (e.g., 10% bare soil, 10% shrub, 80% forest). Fuzzy classification schemes are not currently standardized. Contrary to hard classifiers, soft classifiers do not make a definitive decision about the land cover class to which each pixel belongs. Rather, they develop statements of the degree to which each pixel belongs to each of the land cover classes being considered [34].

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	Soft (Fuzzy)	Hard (Crisp)
Pixel	Each pixel may display multiple and partial class membership.	Each pixel is forced or constrained to show membership to a single class.
Result for spatial resolution data	Provides more information and potentially a more accurate result for spatial resolution data.	The area estimation produces large errors especially from coarse spatial resolution data.
Area of application	It takes into account the heterogeneous and imprecise nature of the real world.	It produce a classification map that consists of hard, discrete categories (e.g., forest, agriculture)

Table 4 : Comparison of soft and Hard Classification

3.5 According to spatial information

3.5.1 Spectral classifiers

Spectral classifier is simple and economic as well as it is considers each pixel individually. It can't describe relation to neighboring pixels. Spectral classes are pixels that are of uniform brightness in each of their several channels. The idea is to link spectral classes to informational classes. However, there is usually variability that causes confusion (forest can have trees of varying age, health, species composition, density, etc.), for this reason pure spectral information is used in image classification. A 'noisy' classification result is often produced due to high variation in the spatial distribution of the same class [35].

3.5.2 Contextual classifiers

In addition to object-oriented and per-field classifications, contextual classifiers have also been developed to cope with the problem of intraclass spectral variations.

Contextual classification exploits spatial information among neighboring pixels to improve classification results.

A contextual classifier may use smoothing techniques, Markov random fields, spatial statistics, fuzzy logic, segmentation, or neural networks. In general, pre-smoothing classifiers incorporate contextual information as additional bands, and a classification is then conducted using normal spectral classifiers, while post-smoothing classification is conducted on classified images previously developed using spectral-based classifiers.

Contextual classification operates on either classified or unclassified scenes. Usually some classification has been done and it reassigns pixels as appropriate based on location (context) [36].

	Spectral Classification	Contextual Classification
Pixel Consideration	Considers each pixel individually.	It reassigns pixels as appropriate based on location (context)
Relation of Pixels	It can't describe relation to neighboring pixels.	It exploits spatial information among neighbouring pixels.
Information used in Classification	Pure spectral information is used in image classification.	The spatially neighbouring pixel information is used in image classification.

Table 5 : Comparison of Spectral and Contextual Classification

3.6 Knowledge-Based Classifiers

Besides the spectral data, expert's knowledge can also play an important role in improving accuracy of the classification of the satellite images. Human experience and knowledge about the topology, geology etc. of the study area can be embodied in the classification procedures to prepare accurate classified maps; such classification is known as knowledge based classification. The most difficult part of knowledge based classifiers is the creation of the knowledge base [37].

3.7 Combination of multiple classifiers

Different classifiers, such as parametric classifiers (e.g. maximum likelihood) and non-parametric classifiers (e.g. Neural network, decision tree), have their own strengths and limitations.

For example, when sufficient training samples are available and the feature of land covers in a dataset is normally distributed, a maximum likelihood classifier (MLC) may yield an accurate classification result.

In contrast, when image data are anomalously distributed, neural network and decision tree classifiers may demonstrate a better classification result. But the integration of two or more classifiers provides improved classification accuracy compared to the use of a single classifier.

A critical step is to develop suitable rules to combine the classification results from different classifiers. Some previous research has explored different techniques, such as a production rule, a sum rule, stacked regression methods, majority voting, and thresholds, to combine multiple classification results [38].

4. Conclusion

Despite the long time spent in developing the classification of remote sensing images, a new problems and new user demands have been accumulated to the existing ones: Existing classification techniques do not suit well to new sensors, huge amount of data demand for new approaches, a wise combination of image analysis techniques emulating the visual interpretation of humans beings and the need to move from the experimental to the operational applications. Moreover, the combination of different classification approaches has shown to be helpful for improvement of classification accuracy.

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