Techniques in Image Classification; A Survey

Mr. S.V.S.Prasad[1], Dr. T. Satya savithri[2] and Dr. Iyyanki V. Murali Krishna[3]

[1] MLRIT

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Abstract

This paper reviews on the current trends, problems and prospects of image classification including the factors affecting it. By the end of the session we will be summarizing the popular advanced classification approaches and methods that are used to improve classification accuracy. The main motive of this review is to suggest a suitable image processing procedure in order to have a successful classification of remotely sensed data into a thematic map.

Index terms— image classification, remote sensed data (rs), training samples (ts), isodata

1 Introduction

he image classification plays an important role in environmental and socioeconomic applications. In order to improve the classification accuracy, scientists have laid path in developing the advanced classification techniques. [1-9] However, classifying a remotely sensed data into a thematic map is still a nightmare because of the following factors such as landscape complexity, image sensing and processing and classification approaches. The review concentrates on recent classification approaches and techniques which are often not available.

2 a) Remote sensing classification process

RS classification is generally a complex procedure which needs many factors to be considered. This procedure includes following steps that begins with the identification of suitable classification system, choosing appropriate training samples, processing of an image and extracting its features, applying a right and indeed classification method, post classification and accuracy assessments.

Airborne and space borne sensor data comes under RS data stream, which varies in spatial, radiometric, spectral and temporal resolutions. In order to have better image classification a suitable RS data needs to be collected, which depends upon strength and weakness of sensor data. In literature the characteristics of remotely sensed data is summarized by **??**10], **??**11] in spectral, radio metric, spatial and temporal resolutions with polarization and angularity.

It is preferred to consider the factors while selecting suitable sensor data as per the user's need, which includes scaling, study area characteristics, availability of various image data and their characteristics, cost, time constraints and analyst's experience in using selected images. Scaling determines the study area; earlier research encountered a problem of image resolution of remotely sensed data in classification. In regular practice, a fine-scale classification system is adopted in order to achieve high spatial resolution data. For example, IKONS and SPOT 5 HRG are at regional level medium spatial resolution data. However, the influence of atmospheric conditions in moist and tropical regions cannot be neglected and they are often an obstacle for capturing the high quality sensor data. Therefore, it always proves to be beneficiary to have multiple sources of sensor data.

3 c) Selection of classification system and training samples

A better classification can be achieved only when we consider a suitable classification system with sufficient number of training samples. Generally, in a wide variety of applications we adopt hierarchy classification systems because different conditions are taken into account. A classification system should consider spatial resolution of selected RS data, compatibility with its previous work, image processing and classification algorithm availability and time constraints. The ultimate goal of choosing any classification system is to satisfy the need of an end user.

The image classification broadly depends on number of training samples and their representativeness. Training samples can be prepared by fieldwork or it can also be obtained from other means such as aerial photographs of fine spatial resolution and satellite images. The results of the classification are affected by the selection of training data, which generally may be based on single pixel, seed or polygon, also affected by fine spatial resolution image data if proper care is not taken. If coarse resolution data is used for classification data then the selection of TS becomes tedious under complex and heterogeneous case studies as it contains large volumes of mixed pixels.

4 d) Data Preprocessing

The image preprocessing is a technique which includes detection, restoration of bad lines, geometric rectification, radio metric calibration, atmospheric and topographic correction. If data is collected from different sources, it is necessary to check the quality before stepping into classification. If the single data image is utilized in classification atmospheric corrections may not be required but on the other hand it becomes mandatory for a multi-sensor data. A variety of correction techniques are presented ??12] ??13] ??14] ??15] ??16] ??17] ??18] ??19] ??20] ??21] ??22] ??23].If the study area includes rugged or mountainous regions a topographic correction is needed, which is detailed ??24] ??25] ??26] ??27] ??28] ??29] ??30].

5 e) Feature Extraction and Selection

The quality of an image classification depends on the selection of suitable variables. A variety of variables used in classification includes spectrum signature, vegetation indices, transformed images, textual information, multi temporal images, multi sensor images and ancillary data. The process of feature extraction is needed in order to minimize data redundancy in remotely sensed data or to excavate specific land cover information, that includes principle component analysis, minimum noise fraction transform discriminant analysis, decision boundary, feature extraction, non parametric weighted feature extraction, wavelet transform and spectral mixture analysis.

6 f) Selection of suitable classification method

The question of choosing a classification method is ambiguous because many factors such as spatial resolution of RD, multi-sensor data, availability of different classification software are involved. Each classification method has its own merits and demerits.

7 g) Post classification processing

Classification confusions arise in the regions such as urban areas, for example, consider between commercial and high intensity residential areas or between recreational grass and crops. In present example to reduce classification confusions we need to consider the property of spectral signature because it is similar to commercial and high intensity residential areas but on the other hand their population densities are different. Pasture and crops are largely located away from residential areas with sparse houses and low population densities, at this stage expert knowledge can be developed based on the relationship between housing or population densities and urban land use classes to help separate recreational grass from pasture and crops.

8 II.

9 Evaluation of Classification Performance

Evaluating the classified results is an important step in classification procedure. The evaluation process may include qualitative evaluation based on expert knowledge to quantitative accuracy based on sampling strategies. The classification accuracy assessment is the most common approach for the evaluation of classification performance ??31] ??32].

10 a) Classification of accuracy assessment

By the knowledge of sources of errors, classification accuracy assessment can be implemented in addition to classification error, position error, which resulting from registration, interpolating error and poor quality of training which may affect the classification accuracy. The classification accuracy assessment includes three basic steps 1.Sampling design, 2.Response design,3. Estimation and Analysis procedures

11 b) Advanced classification procedures

The advanced classification procedures such as neural networks, fuzzy sets and expert systems are highly applied for image classification. In general image classification approaches it can be grouped as supervised or unsupervised, parametric and nonparametric or hard and soft classifiers or per pixel, sub pixel, per field. Table provides brief description of these categories.

12 c) Use of multiple features of remote sensed data

Any remote sensed data generally contains many unique and special spectral radio metric temporal and polarization characteristics; the effective use of these features can improve the classification accuracy. The summary of table 3 presents the research efforts in order to improve the classification accuracy by considering the features of remote sensed data.

13 III.

14 Discussions a) Uncertainties in image classification

Uncertainties in image classification occur at different stages, influence classification accuracy. Improving and understanding the stages those contribute to uncertainty results in quality image classification.

15 b) Impact of spatial resolution

Spatial resolution is an important factor that affects classification details and accuracy, which influences the selection of a classification approach. Various reduction techniques have been developed and presented by different authors in their literature.

16 c) Selection of suitable variables

In practice, making a complete use of multiple features of different sensor data, implementing feature extraction and selecting variables as input for a classification procedure becomes important.

IV.

17 Conclusion

This study helps upcoming scientists and researchers for opting a suitable classification procedure in their specific study. In our presentation we have concentrated extensively on the work done from the past decade that includes 1. Development and advanced classification algorithms such as sub pixel, per field and acknowledged based classification algorithms; 2. We have considered various remote sensing features including spectral, spatial, multi temporal and multi sensor information; 3. Incorporating an ancillary data into classification procedures that includes topography, soil, road and census data. [124], [125] [107], [126], [97], [127], [128] Visual fuzzy classification based on use of exploratory and interactive visualization techniques [129] Multi temporal classification based on decision fusion [130] Supervised classification with ongoing learning capability based on nearest neighbor rule [131] Combinative approaches of multiple classifiers Multiple classifier system (BAGFS: combines bootstrap aggregating with multiple feature subsets) [132] A consensus builder to adjust classification output (MLC, expert system, and neural network) [133] Integrated expert system and neural network classifier [133] Improved neuro-fuzzy image classification system, Spectral and contextual classifiers, Mixed contextual and per-pixel classification, Combination of iterated contextual probability classifier and MLC [134],[116], [135], [136] Combination of neural network and statistical consensus theoretic classifiers [137] Combination of MLC and neural network using Bayesian techniques [138] Combining

18 Use of textures

First-, second-, and third-order statistics in the spatial domain; texture features from the texture spectrum and from grey level different vector [144] Grey-level co-occurrence matrices(GLCM) [145], [146], [147], [148], [149] Co-occurrence matrices, grey-level difference, texture-tone analysis ,features derived from Fourier spectrum, and Gabor filters [150] GLCM, grey level difference histogram, sum and different histogram [151], [152] Fractal information [153], [154] Triangulated primitive neighborhood method, Semi variogram, Geo statistical analysis, Gabor filtering [155], [156], [157], [158] [194], [195], [109], [196], [197], [97], [198], [199] Hyper -spectral data AVIRIS [200], [201], [202], [203], [204], [205] HyMap hyper spectral digital data, DAIS hyper spectral data, EO-1 Hyperion, Data obtained from Field Spec Pro FR spectro radiometer [127] [206] [207], [208] Based on topography, Based on census data, Based on illumination and ecological zone, Based on shape index of the Patches [215], [210], [216], [217] Post classification processing Kernel-based spatial reclassification [218] Using zoning and housing density data to modify the initial classification result, Using contextual correction, [213], [219] Using filtering based on co occurrence Matrix, Using polygon and rectangular mode filters, Using expert system to perform post classification sorting, Using knowledge-based system to correct misclassification [220], [221], [222], [223] Use of multisource data Spectral, texture, and ancillary data (such as DEM, soil, existing GIS-based maps)

[123], [224], [225], [137],[226],

[227],[7], [228] References Références Referencias [1] [2] [3]

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1

Criteria	Categories	Characteristics	Example of classifiers
Whether training samples are used or not	Supervised classification approaches	Land cover classes are defined. Sufficient reference data is available and used as training samples. The signatures generated from the training samples are then used to train the classifier to classify the spectral data into a thematic map	Maximum likelihood, minimum distance, artificial neural network, decision tree classifier.
	Unsupervised classification approaches	Clustering-based algorithms are used to partition the spectral image into a number of spectral classes based on the statistical information inherent in the image. No prior definitions of the classes are used. The analyst is responsible for labeling and merging the spectral classes into meaningful classes.	ISODATA, K-means clustering algorithm
Whether parameters such as mean vector and covariance matrix are used or not	Parametric classifiers	Gaussian distribution is assumed. 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.	Maximum likelihood, linear discriminant analysis.
	Non-Parametric classifiers	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.	Artificial neural network, decision tree classifier, evidential reasoning, support vector machine, expert system.
Which kind of pixel	Per-pixel classifiers	Traditional classifiers typically develop a signature by combining the spectra of all	Most of the classifiers, such as maxi-

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Category	Advanced classifiers	References
Per-pixel algorithms	Neural network	[33], [34], [35],[36], [37], [38], [39], [40], [41], [42], [43]
	Decision tree classifier, Spectral angle classifier, Supervised iterative classification (multistage classification)	[44], [45], [46],[47], [32],[8],[48],[49],[50], [51],[4]
	Enhancement-classification approach,MFM-5-Scale (Multiple-Forward-Mode approach to running the 5-Scale geometric-optical reflectance model)	[52],[53]
	Iterative partially supervised classification based on a combined use of a Radial Basis Function network and a Markov Random Field approach	[54]
	Classification by progressive generalization Support vector machine	[31],[55], [56], [57], [58],[59],[60], [61], [62], [63]
	Unsupervised classification based on independent component analysis mixture model, Optimal iterative unsupervised	[64],[65], [66]
	Model-based unsupervised classification, Linear constrained discriminant analysis	[67], [68] ,[69], [70]
	Multispectral classification based on probability density functions,	[71],[72],[73][74],[75],[76], [77]
	Layered classification, Nearest-neighbor classification, Selected pixel classification	
Sub pixel algorithms		

[Note: Imagine sub pixel classifier, Fuzzy classifier, Fuzzy expert system [78], [3],[79],[80],[81], [82] Fuzzy neural network, Fuzzy-based multi sensor data fusion classifier, Rule-based machine-version approach [3], [83],[84], [80], [85], [86], [87] Linear regression or linear least squares inversion [88],[89] [120],[121],[122], [123],[7],]

Figure 2: Table 2 :

3

Method	Features	References

Figure 3: Table 3 :

4

Method	Features	References
Use of ancillary data	DEM Topography, land use, and soil Maps	[209] [210]
	Road density, Road coverage, Census data	[211] [212] [213], [214] [173]
Stratification		

Figure 4: Table 4 :

Techniques in Image Classification; A Survey Techniques in Image Classification; A Survey Techniques in Image Classification; A Survey Techniques in Image Classification; A Survey Techniques in Image Classification; A Survey Techniques in Image Classification; A Survey Techniques in Image Classification; A Survey

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