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Review On Conventional and Advanced Classification Approaches in Remote Sensing Image Processing

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***Abstract*—** Nowadays remote sensing image classification process has been most commonly used for object identification. It identifies the object in the remote sensing images by assigning the land cover classes to pixels. In this paper, a review on conventional and advanced remote sensing image classification techniques such as supervised, unsupervised, per pixel, sub pixel and object based image analysis processes has been provided. Further, a brief description about the effective features of different image classification algorithms like Fuzzy classifier, classification based on Artificial Neural Network (ANN), classification based on Support Vector Machine (SVM), Evolutionary Algorithms (EA) and Optimum Path Forest classification algorithms were also given. In the next section of paper various classification methodologies with their characteristics and examples of classifiers are explained. Moreover, this study compares the frequently used image classification algorithms and suggests the remote sensing image classifier to choose the best image classification technique based on the performance of classification that improves the accuracy range.

***Keywords*—**Remote sensing, Image classification, ANN, SVM, Optimum Path Forest.

I. INTRODUCTION

Remote sensing has become one of the best approaches for earth observation. It has the ability to collect images and obtain data's about the object using sensors on unmanned aerial vehicle, satellites, aircrafts or without having any physical connection . Some of the real world applications used by remote sensing are global mapping, plantation observation, monitoring the quality of water, climatic studies about environment and urban areas, identification of fires in forest, exploration of minerals, detection of oil spills, and accuracy in horticulture identification [1]. Remote sensing images cover a wide geographic zone with high time-based frequency and it provides a chance for obtaining information from required place by using classification method. At the time of 1980 to 1990, most of the classification methods utilized the image pixel as fundamental unit of analysis, where each and every pixel is marked as single. Image classification is denoted as the technique of classifying the data from vast satellite images by sorting the image pixel values. Main concept behind the image classification is that various attributes on the earth's surface have different spectral reflectance [2]. With the help of pixel as fundamental analysis unit, a sequence of classification methods have been developed, some of the classification methods are supervised, hybrid classification and unsupervised [3], [4].

Mostly in modern classification methods high resolution (HR) and very high resolution (VHR) remotely sensed images has been used which is obtained with the help of World View, IKONOS and QuickBird. The present issues, practices and views of image classification and the major developments in classification algorithms are analyzed in [5]. The methods of digital image processing for extracting features from HR satellite images are studied [6]. Brief theoretic information about various image classification algorithms are sketched [7]. Different studies on satellite image classification approach are described [8]. The highly utilized classification methods which are mainly used to advance the classification accuracy, also, it deemed different remote sensing characteristics features like multi temporal, spectral, multi sensor information, spectral, in addition ancillary data are depicted [9]. Several post classification methods, spectral contextual classification and supervised classification algorithms are investigated [10]. Continual development of innovative classification algorithm and methods in modern years requires a brief study for directing or choosing an appropriate classification process. This study offers a detailed description of the merits, competence and confines of these classification methods.

Major inspiration behind this study is to support the analyst, particularly for those who are fresh to the remote sensing field for selecting an appropriate classification method to analyze remotely sensed satellite imagery. This study provides the recent improvements in classification algorithm and also discussed about the frequent issues related with them.

The rest of this paper is organized as follows. Section II provides an introduction about image classification. A review on Remote sensing image classification techniques are given in Section III. Section IV and Section V analyze various conventional and advanced image classification approaches. Different classification algorithms are presented under Section VI and Section VII concludes this paper.

II. IMAGE CLASSIFICATION PROCESS

Basically image classification is a process of pixel classification which obtains a set of labels. For humans, classifying the object is an easy task but it is complicated for machines. Development of high power computers in accessibility of low cost and high quality output has created attention on image classification approaches. Figure 1 shows the flow diagram of image classification process. Object classification, image pre-processing, feature extraction, image sensors and object segmentation are the steps involved in image classification process. This image classification system contains database which includes various predefined patterns to identify a particular object and categorize it. Image classification acts as a unique demanding task in different application domains such as remote sensing, Navigation process, industrial visual inspection, surveillance purposes, medical application and robot navigation.

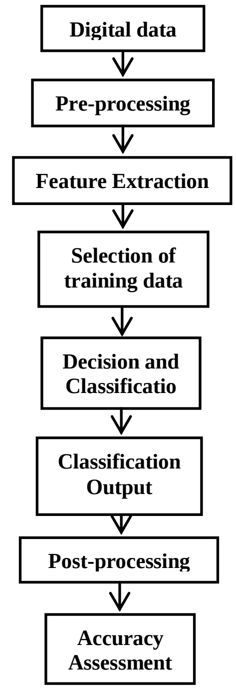

Figure 1. Flow diagram of Image classification process

III. REMOTE-SENSING CLASSIFICATION METHODS

A. Data Pre-processing

Before moving into the classification phase, it is essential to examine the standard of remote sensed information. Atmospheric and topographic corrections, geometric rectification, radiometric calibration and restoration of bad lines are involved in image pre-processing. No atmospheric correction is essential, if one information source is exert in classification. A topographic correction is required when the review area belongs to rugged or mountainous regions and further an extensive range of correction methods are also presented [11], [12].

B. Feature extraction and selection

Classification accuracy can be enhanced by using attributes or features of images as input information to classification techniques. Large number of variables are existing which includes surface roughness, vegetation indices, ancillary data (for non-spectral geographical information), transformed images, textual information, height texture or multi-temporal images, spectrum signature, multi-sensor images, shape and size of objects. Preference of attribute sets for a classification method is essential in order to minimize dimensionality of datasets without scarifying accuracy. On the other side, some general issues related with HR data like shadows and variations in spectral values of the land surface are required to compensate them. For feature extraction, numerous techniques are exerted such as non-parametric weighted feature extraction (NPWFE), feature extraction (FE), principle component analysis (PCA), decision boundary (DP), wavelet transform (WT), transform discriminant analysis (TDA), spectral mixture analysis (SMA) and minimum noise fraction (MNF).

C. Selection of training samples

The selection of an appropriate algorithm together with adequate amount of training samples should provide better classification of samples. The training samples are often obtained from fieldwork or from other data sources like aerial or satellite images with fine spatial resolution that depends upon single pixel, seed or polygon. The selection of training samples in coarse resolution data is difficult because of the presence of mixed pixel region. The mixed pixel regions are formed due to the occurrence of various classes in single pixel. The training samples are generated to locate a group of statistics that determines the spectral behavior for each land cover class to be categorized in the image data. Later, the algorithm is trained well with the help of training samples. According to Hughes phenomenon, during parametric classification, the dimensionality of stable sized-sample could increases beyond certain limit and the precision of model parameter decreases. Thus, the amount of training pixel is not significant and parametric classification is not suitable to incorporate ancillary data [13]. Based on the difficulties of problem under consideration, the range of training sample sets is [30 * Xi *(Xi + 1)] and [60 * Xi *(Xi + 1)], in that, Xi represent the input layers or features [14].

IV. CLASSIFICATION APPROACHES

A number of classification techniques have been established and employed. The satellite image classification techniques are broadly categorized into: (a) unsupervised (b) supervised and (c) hybrid. These methods have their own merits and demerits. For efficient classification of satellite images, the analyst manually detects each cluster labels on land cover class since multiple clusters denotes individual land cover class. Then the analyst combines the clusters into single land cover class. Unsupervised classification is used under such situations if there is no training samples are available [15]. ISODATA (Iterative Self-Organizing Data Analysis Technique) and K-means are the two frequently utilized clustering approaches. These two approaches depend upon pixel- statistics and integrate no prior knowledge of theme characteristics under investigation.

On the other hand, in supervised classification the analyst describes small representative samples for individual land cover class known as training samples [16]. The classification accuracy highly relies on the samples utilized for training. Image classification approach takes the training data sets to detect the land cover classes in the whole image. Some common supervised classification algorithm are minimum distance (MD), Mahalanobis distance (MhD), parallelepiped (PP), maximum likelihood classifier (MXL), K-nearest neighbor (KNN), SVMs, and spectral angle mapper (SAM) [17]. The major steps of image classification in supervised and unsupervised approaches are shown in Figure 2.

The supervised technique has some benefits over the unsupervised technique. In supervised classification, initially the valuable information are separated and then the spectral separability is inspected whereas in unsupervised classification, a computer defines the spectrally seperable classes and then determines the valuable information. However, it is easy to implement unsupervised classification, though it does not need any analyst-dependent training samples and is extensively present in statistical software and image processing packages. Furthermore, it achieves higher classification accuracy by spontaneously transforming the raw image data sets into valuable information [18]. But one of the limitations of unsupervised approach is that the entire classification is to be repeated while adding new data sets.

Both the supervised and unsupervised classifications are alternative approach to each other but they are often integrated with more than one method to develop a hybrid system [19]. With supervised and unsupervised approaches, still it is challenging to attain satisfactory outcomes for higher spatial and spectral resolution characteristics based new generation images [20].

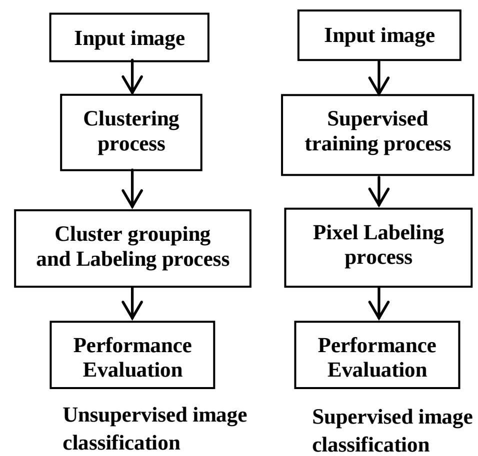

Figure 2. Processing steps of a) Unsupervised method and b) Supervised method

V. ADVANCED CLASSIFICATIONS APPROACHES

A. Image classification based on pixel-wise approach

In a typical remote sensing image classification method, pixel-based image classification strategy assumes that each pixel is labelled as single land use cover type [21-23]. According to this method, the remote sensing images are considered to be a collection of pixels with spectral information; spectral variables and their transformations are given as input to the per-pixel classifiers. Pixel-based image classification approaches are categorized into two sets: supervised classification and unsupervised classification. The supervised classification is further divided into: Maximum Likelihood Classifier (MLC), Minimum Distance-to-Means Classifier, Mahalanobis Distance Classifier, Parallelepiped and K-Nearest Neighbors Classifier, etc. [24-28]. The comparison of SVM with other methods showed assured better/ improved classification accuracy [29]. Nowadays, machine learning methods are established to enhance the knowledge learning process [30-33].

B. Image classification based on sub-pixel based approach

The pixel based image classification approach in remote sensing assumes that there is only a single land use land cover type in individual pixels of image. Nevertheless, this assumption is unacceptable for coarse and medium resolution images due to landscape diversity as compared to spatial resolution remote sensing imagery. Therefore, the use of pixel-wise hard classifications reduces the classification accuracy of land use cover maps [34]. An alternative method of pixel based image classification is sub-pixel classification that accurately determines the areal part of individual land use land cover type [35]. Major sub-pixel classifications like fuzzy classification, neural networks, regression modelling, regression tree analysis and spectral mixture analysis are designed to report the mixing pixel problem. In fuzzy demonstration, each pixel that obtains partial membership of all classes as well as the equivalent areal proportion of the classes is estimated accordingly [36-40].

Sub-pixel analysis technique is established to measure the quantity of urban impermeable surfaces and urban vegetation [41]. A multiple end member spectral mix investigation method to map chaparral, a shrub land plant communal in the Santa Monica Mountainous region is suggested in [42]. A four-end member spectral mix investigation process to evaluate the sub-pixel percent urban impervious surfaces is created in [43]. A fuzzy-spectral mix analysis framework is offered in [44]. Compared to traditional SMA techniques, fuzzy spectral mix analysis framework achieved fuzzy mean and fuzzy covariance using training data sets derived via SMA, and applied with conventional fuzzy classifiers. Table 1 gives the comparison of both conventional and advanced classification methods.

C. Object based image classification

When comparing sub-pixel and per-pixel classification strategies with object based image classification, object based image classification affords a new way to categorize remote sensing images [45-47]. Other than considering the image as a distinct pixel, geographical objects are found to be the major source of analysis in object-based image classification approaches. Object-based techniques create an image object via image segmentation and classify the images according to objects rather than pixels [48]. Using image segmentation, the image objects are generated with contextual, spatial, spectral and textural data. The objects generated with these data are classified on the basis of spectral and other related decisive factor. Object based processes are found to be more suitable for VHR remote sensing imagery. Numerous studies have proven the higher classification accuracy of object-based methods [49]. An advanced version of object-based method is used to recognize the radius of the remotely sensed data [50]. A resource-limited AIS supervised classifier with Artificial Recognition Balls (ARBs) concept is also presented to deal with the remote sensing images to perform classification more effectively [51].

VI. ADVANCED CLASSIFICATION ALGORITHM

The advanced classification algorithms used in the image classification techniques ensure better accuracy and improves the quality of remote sensing images. Major advanced classification algorithms that are commonly used in remote sensing image processing are SVMs, ANN and CTs, which outdates the conventional classifiers with their high performance. So modified algorithms are well suited for incorporating non-spectral data into the classification process. Table 2 specifies the advantages and disadvantages of both conventional and advanced classification Algorithms

A. ANN based classification

The approach starts with providing the training samples as input, pixel by pixel in order to train the ANN, thereby acquiring the conditional probability of a certain pixel in the output layer. It shows better results and performance, than other classifiers used in image classification process [52-54]. It achieves lower computational cost when dealing with ANN based semi-supervised classifier than the two kernel-based methods such as Transductive SVM (TSVM) and Laplacian SVM (LapSVM) [55], [56]. ANN is supposed to suffer by over-fitting because of the high dimensionality of remote sensing images and the difficulties experienced during the acquisition of training samples. To resolve the inconsistencies faced with ANN, Evolutionary Artificial Neural Network (EANN) is adopted [57]. EANN is a well-trained network structure, which has the ability to acclimatize complex remote sensing data with high robustness. Furthermore, Evolutionary Programming (EP) is used to develop ANN architecture as well as the connection weights. Nowadays EANN is commonly used to identify the crops from the remotely sensed data. Pareto Differential Evolution (PDE) algorithm is used in multi-objective evolutionary neural network to achieve efficient feed-forward Multilayer Perceptron (MLP) neural network [58].

Table 1. Comparison of conventional classification methods with advanced classification methods

Classification Methodologies	Characteristics	Examples of classifiers
Parametric	● Normal distribution of data ● Prior Knowledge of class density functions	● Maximum Likelihood classification ● Unsupervised classification
Non-Parametric	● No need of any prior assumptions	● Nearest-neighbour classification ● Fuzzy classification ● Neural networks ● SVM
Supervised	● Analyst detects the training sites to represent in classes ● Each pixel is categorized on the basis of statistical analysis	● Maximum Likelihood, ● Minimum Distance ● Parallelepiped classification
Unsupervised	● Earlier ground information is unknown. ● Pixels with same spectral properties are clustered according to exact statistical criteria	● ISODATA and K-means etc.
Pixel based	● Each pixel is assumed pure and typically labelled as a single land use land cover type	● Unsupervised, example: k-means, clustering ● Supervised example: Maximum likelihood ● Machine learning example: ANN, SVM etc
Sub pixel based	● Pixel quantity of each class is calculated	● Fuzzy classification ● Neural networks ● Regression modelling ● Spectral mixture analysis ● Fuzzy spectral mixture analysis
Object based	● Geographical objects are considered as the basic unit. ● Additional characteristics such as object texture, shape and relations to adjacent regions can be used. ● Appropriate for HR imagery applications. ● Classification accuracy is decreased due to over and under segmentation.	● Image segmentation ● Object based image analysis
Hybrid Approaches	● Includes expert systems and artificial intelligence. ● Combine the advantages of multiple classifiers	● Set of laws for voting ● Bayesian formalism ● Multiple ANN.

B. EA based classification

EA based classifiers are non-parametric methods usually doesn't made supposition on the allocation of remote sensing data. Coupled Simulated Annealing (CSA) with Simulated Annealing (SA) is employed to enhance the range of population in the remote sensed data [59]. EAs are used to optimize the traditional artificial immune network, but in later days it starts focusing on the classification of remote sensed data [60]. Furthermore, Genetic Fuzzy Rule Based Classification System (GFRBCS) is applied to develop classification rules for the remote sensing images [61], [62]. Genetic Programming (GP) is used to generate new vegetation indices including Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI) [63].

C. Classification based on Support vector machine and fuzzy concept

A new SVM technique is designed and used in the classification process of the remote sensing satellite images in [64-66]. It works based on the principle of statistical learning theory [67]. SVM exhibits better results for hyper-spectral remote sensing data and also it is well applicable for various types of data include Landsat multispectral data [68-70]. While on dealing with fuzzy classifiers, for each and every pixel in a class it generates a fuzzy set membership [71].

D. Classification based on Optimum path forest

OPF classifiers are used as a modern image classification tool, whereas it represents a graph-based framework [72], [73]. The function of OPF in the field of image processing is described as Image Foresting Transform (IFT) in [74]. Here IFT works based on the concept of Dijkstra's shortest path algorithm with minor modifications. Additionally OPF provides better results when used by both the Supervised and Unsupervised Learning variations. Recently OPF is used to identify the kind of disease in medical field, forest monitoring etc [75-77].

Table 2. Advantages and Disadvantages of both conventional and advances classification Algorithms

Classification methods	Advantages	Disadvantages
ISODATA	Processing speed is high and easy to handle	Requires more number of parameters.
K-Means	Fast and easy approach	Initiates by the number and the position of initial cluster.
K-Nearest Neighbour	Simple to process	For larger training set, the computation cost is high
Minimum Distance	Processing speed is high and easy to handle	Process based on mean value
Parallel pipelining	Fast and simple approach to process	Results accuracy will low, if overlapping occurs.
Maximum Likelihood	Sub pixel classifier	a) Consumes more time b) Can't use unless the dataset is probably distributed c) Inadequate ground truth data
	a) Handles noisy inputs effectively b) High computational cost c) Ability to represent functions including ANDOR and NOT	a) Overfitting problem occurs b) Hard to select the network architecture type. c) It is semantically poor
	a) Reduce the problem of overfitting b) Computational complexity also get reduced c) Ease to handle the decision rule complexity.	a) Complex to understand the concept of algorithm b) Difficult to find the optimal parameters c) Requires more time to train the training set.
Fuzzy Measure	a) Handles uncertainties effectively b) Stochastic relationships are identified	Requires prior knowledge to obtain good and exact results
	a) Executes the training phase at high speed b) Decision making is done based on global decisive factor	

VII. CONCLUSION

In the field of remote sensing image classification, more advanced progress has been made over the last few decades with the recent advancement of different classification approaches and algorithms. However, this review provides an idea about numerous conventional and advanced image classification approaches. Furthermore, we provide guidance about various classification approaches like ANN, EA, SVM and OPF. Recently, the remote sensing image classification field has become an important topic for research work. But the researchers often found it difficult to select the suitable image classification approach because of insufficient guidance. Thus, this review brings out the efficiency of using different image classification approaches and helps the researches to choose a best approach according to their application. Moreover, a comparison has been made for better understanding, which helps to select the proper choice of image classification approach.

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