ISSN No. 0976-5697
Volume 3, No. 7, Nov-Dec 2012
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info

A survey on RSI classification techniques

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Abstract: Remote sensing image (RSI) classification is an important content of RS research area in geological survey, mineral exploration, geological evaluation and disaster monitoring and basic geological research. RSI classification, which is a complex process that may be affected by many factors, used to classify different features available in the image. The present paper investigates the process of the RSI classification, current practices, limitations, and its future. The main emphasis is given to summarize the major classification algorithms, approaches and the techniques used for improving classification accuracy. In addition, some important issues affecting classification performance are also discussed. This investigation suggests that developing computationally efficient algorithms for image classification without compromising the classification accuracy is of primary importance. Effective use of multiple features of remotely sensed data and the selection of suitable RSI classification algorithms are especially significant for enhancing classification accuracy. In the existing algorithms such as Parallelepiped, minimum distance to mean, maximum likelihood, nearest neighborhood, k-mean, and ISODATA, etc. cited in this paper, all pixel data of image are used as feature vector for extracting the information from image, but the threshold values of pixels based on BTC, can be used for better performance. Integration of remote sensing with geographical information systems (GIS) and expert classification system is emerging as an appealing research direction.

Keywords Remote Sensing Image (RSI), geographical information systems (GIS), efficient algorithms, classification accuracy, etc.

I. INTRODUCTION

In the recent era of advancement, Remote Sensing (RS) techniques have a wide range of applications from military to farm development. It is a science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. A principal application of remotely sensed data is to create a classification map of the identifiable or meaningful features or classes in a scene. Remote sensing research focusing on image classification has long attracted the attention of the RS community because classification results are the basis for many environmental and socioeconomic applications. Scientists and practitioners have made great efforts in developing advanced classification approaches and techniques for improving classification accuracy [1, 2, 3, 4, 5, 6].

However, classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image-processing and classification approaches, may affect the success of a classification. Even though, huge information is existed in literature concerned with image classification [7, 8], a comprehensive up-to-date review of classification methods and techniques is not available. The rapid growth of new classification methods, algorithms and techniques in the modern era of technology necessitates such a review, which will be highly valuable for guiding or selecting a suitable classification procedure for a specific study.

The focus of this paper are on providing a summarization of available classification methods, techniques and algorithms used for improving classification accuracy, and on discussing important issues affecting the success of image classifications. Common classification algorithms, such as K-means, parallelepiped, minimum distance, nearest neighborhood, and maximum likelihood, are discussed thoroughly with their advantages and limitations. Also, the need for efficient algorithms with latest improvement in the classification approach has been discussed, which will help in various application such as architecture design, geographic information system, whether forecast, etc.

II. RSI CLASSIFICATION PROCESS

Remote sensing image (RSI) classification is a complex process, which includes determination of a suitable classification system, selection of training samples, image preprocessing, feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment as a major steps. The selection of suitable sensor data is the first step. Remotely sensed data vary in spatial, radiometric, spectral, and temporal resolutions. Understanding the strengths and weaknesses of different types of sensor data is essential for the selection of suitable RS data. Preprocessing of data acquired is another step of RSI classification process.

It includes the detection and restoration of bad lines, geometric rectification or image registration, radiometric calibration and atmospheric topographic corrections. Feature selection and extraction are central issues when dealing with high dimensional datasets because of the curse of dimensionality. For successful classification, a sufficient number of training samples with suitable classification system are pre-requisites. Many factors, such as spatial resolution of the remotely sensed data, different sources of data, a classification system, and availability of classification software must be taken into account when selecting a classification algorithm for use. Different classification algorithms have their own merits. The question of which classification approach is suitable for a specific study is not easy to answer. Post-classification processing is one of important steps to reduce the noises and to improve the quality of classifications [3]. Classification accuracy

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assessment is the last and essential step of classification to evaluate the performance of classification.

III. RSI CLASSIFICATION ALGORITHMS

RSI classification is a very important application of digital image classification, which has many similarities as universal image classification. However, remote sensing images have some unique characteristics, if computer can be used to classify automatically remote sensing images according to certain meaning, it will be easier to extract and analyze vast amounts of remote sensing data. Classification of remotely sensed data is used to assign corresponding level with respect to groups with homogeneous characteristics, with the aim of discriminiating multiple objects from each other within the image. Classification will be executed on the base of spectral or spectrally defined features, such as density, texture etc. in the feature space. Switzer was the first to treat classification of spatial data [9]. In the literature, many image classification techniques have been proposed, although commercially only a few techniques are frequently found. Although, many classification techniques have been developed, which is suitable for features of interest in a given study area is not fully understood. The computer classification methods of remote sensing images are divided into two types: statistical pattern method and syntax pattern method. The common classification method is statistical identification pattern, such as maximum likelihood method and K minimum distance discrimination method. The statistical classification methods of remote sensing images are divided into two types: unsupervised classification and supervised classification or parametric and nonparametric, or hard and soft (fuzzy) classification, or per-pixel, subpixel, and perfield [10, 11]. Unsupervised classification is the process that for remote sensing images without prior knowledge, only depends to the statistical difference of combination of different spectroscopic data, and then validates ground objects according to properties of various classified objects.

In supervised image classification training stage is required, which means first we need to select some pixels form each class called training pixels. Find the characteristics of training pixels and also find other pixels which have same characteristics, this way image classification can be done. In unsupervised image classification, no training stage is required, but different algorithms are used for clustering. Numerous factors affect the classification results, among which important ones being the objective of classification, the spectral and spatial characteristics of the data, the natural variability of terrain conditions in geographic region, and the digital classification technique employed [12]. The classification algorithms can be per-pixel, sub pixel, and per-field. Per-pixel classification is still most commonly used in practice. However, the accuracy may not meet the requirement of research because of the impact of the mixed pixel problem. The 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. Unsupervised methods aim at clustering the image pixels into a pre-defined number of groups by measuring their similarity. One of the main applications for such methods is change detection, where the method should be able to recognize changes in real time [13, 14]. The per-pixel classification algorithms can be parametric or non-parametric. The parametric classifiers assume that a normally distributed dataset exists, and that the statistical parameters (e.g. mean vector and covariance matrix) generated from the training samples are representative. However, the assumption of normal spectral distribution is often violated, especially in complex landscapes. In addition, insufficient, non-representative, or multimode distributed training samples can further introduce uncertainty to the image classification procedure. Another major drawback of the parametric classifiers lies in the difficulty of integrating spectral data with ancillary data. The maximum likelihood may be the most commonly used parametric classifier in practice, because of its robustness and its easy availability in almost any image-processing software. With non-parametric classifiers, the assumption of a normal distribution of the dataset is not required. No statistical parameters are needed to separate image classes. Non-parametric classifiers are thus especially suitable for the incorporation of non-spectral data into a classification procedure [15, 16].

Various supervised classification algorithms may be used to assign an unknown pixel to one of a number of classes. The common classification algorithms or classifiers are Parallelepiped, Minimum distance to mean, Maximum likelihood and Nearest neighborhood, K-mean, ISODATA, etc. The details about these algorithms can be found in [17]. The analysis of various classification algorithms studied by many researchers found in literature [5, 18]. A comparative study of different classifiers is often conducted to find the best classification result for a specific study [19, 2] for improving classification performance [20]. The comparative analysis of various supervised and unsupervised image classification algorithms have been carried out by [5, 21, 22, 23].

The Parallelepiped is a very simple supervised classification algorithm. In this, two image bands are used to determine the training area of the pixels in each band based on maximum and minimum pixel values. Although parallelepiped is the most accurate of the classification techniques, it is not most widely used. It leaves many unclassified pixels and also can have overlap between training pixels [5, 24, 6]. The RSI classification algorithm based on the minimum distance decision rule is minimum distance supervised classification algorithm. It is based on the feature space distance as the basis of pixel classification [25]. The minimum distance classification is simple in principle, classification accuracy is not high, but has the fast calculation speed; it can be used in the quick scan classification [26]. Similar to minimum distance classification, Mahalanobis distance is also based on the minimum distance decision rule except that the covariance matrix is used. After comparison of different classification methods and their performances, [5] found that Mahalanobis Minimum Distance classifier performed the best for classification remotely sensed data.

The nearest-neighborhood algorithm is simplest of all algorithms for predicting the class of a test example. This algorithm is often useful to take more than one neighbour into account so the technique is more commonly referred to as k-Nearest Neighbour (k-NN) Classification where k nearest neighbours are used in determining the class [18].

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Nearest neighborhood method is commonly used in remote sensing, pattern recognition and statistics to classify objects into a predefined number of categories based on a given set of predictors. Luis et al. pointed out several shortcomings of nearest-neighborhood algorithm [27] such as its performance highly depends on the selection of k, pooling nearest neighbors from training data that contain overlapping classes [28, 29, 30]. Further, Luis et al. [27] studied Modified k-NN technique and observed substantial improvement with regard to the classification accuracy compared with other approaches. Maximum Likelihood Classification (MLC) is perhaps the most widely used classification method of classification in remote sensing in which a pixel with the maximum likelihood is classified into the corresponding class [31, 24, 6]. MLC algorithm uses Bayes' rule and a classification method that minimum incorrect probability in terms of statistical rules. This Classification uses the training data by means of estimating means and variances of the classes, which are used to estimate probabilities and also consider the variability of brightness values in each class [5]. Ali and Talebzadeh pointed out limitations of classification by MLC and suggested MLC Classification method using a-priori information to improve the accuracy [31]. It is claimed by [32, 33] that Maximum likelihood classifier (MLC) was limited by utilizing spectral information only without considering contexture information.

The unsupervised standard K-means algorithm [34] is one of the most widely used and simplest clustering algorithms, which utilize unsupervised learning. It is a basic method in analyzing RS images, which generates a direct overview of objects. Usually, such work can be done by some software (e.g. ILWIS, ERDAS IMAGINE) in personal computers (35). In this algorithm, each point is assigned to only one particular cluster. The procedure follows a simple, easy and iterative way to classify a given data set through a certain number of clusters fixed a priori. The rule of K-means algorithm is that makes sum of squares of distance that multi-pattern point to center of category. The basic idea is that moves the centers of every category by iteration until get the best clustering results. [24,6] studied a remotely sensed image classification method based on weighted complex network clustering using the traditional K-means clustering algorithm and observed an increase of 8% in accuracy compared with the traditional K-means algorithm and the Iterative Self-Organizing Data Analysis Technique (ISODATA). ISODATA is "Iterative Self- Organizing Data Analysis Technique". ISODATA realizes clustering by using minimum spectral distance equation. The essence of ISODATA is the process that gets initial categories as "seeds" and cluster automatic iteration according to a discriminate rule. As such, clustering is a method of grouping data objects into different groups, such that similar data objects belong to the same group and dissimilar data objects to different clusters [25,26]. Image clustering consists of two steps the former is feature extraction and second part is grouping. For each image in a database, a feature vector capturing certain essential properties of the image is computed and stored in a feature base. Clustering algorithm is applied over this extracted feature to form the group. Clustering using Block Truncation Coding (BTC) and colour moments to classify images into various categories were studied by [36, 37, 38, 39, 40].

Of late, [4] uses CBIR using photographic images of human being, animals, and natural scenery. They stated that BTC based features are one of the CBIR methods using color features of image. Further, they suggested that, instead of using all pixel data of image as feature vector for extracting the information from image, the six features based on mean of each and threshold can be used, resulting into better performance and if increased the no. of feature vector get better performance. Thus, the performance of CBIR system depends on the precision and recall. Silvia et al. used BTC to extract features for image dataset and conducted K-Means clustering algorithm to group the image dataset into various clusters [41]. They found that the performance of BTC algorithm's as superior to cluster images into groups.

As such, the basic concepts of BTC were born on March 17, 1977 in the office of O. Robert Mitchell at Purdue University (42). BTC is a relatively simple image coding technique developed in the early years of digital imaging more than 30 years ago. It is an efficient image coding algorithm developed in 1979 during the initial years of image processing [42, 43]. Although, BTC is simple technique, it has played an important role in the history of digital image classification in the sense that many techniques have been developed based on BTC or inspired by the success of BTC [44, 4]. The method first computes the mean pixel value of the whole block and then each pixel in that block is compared to the block mean. If a pixel is greater than or equal to the block mean, the corresponding pixel position of the bitmap will have a value of 1 otherwise it will have a value of 0. Two mean pixels values one for the pixels greater than or equal to the block mean and the other for the pixels smaller than the block mean will also calculated. At decoding stage, the small blocks are decoded one at a time. For each block, the pixel position where the corresponding bitmap has a value of 1 is replaced by one mean pixel value and those pixel positions where the corresponding bitmap has a value of 0 is replaced by another mean pixel value. The BTC technique can be extended to higher levels by considering multiple threshold values to divide the image pixels into higher (upper) and less than or equal to (lower) threshold [39].

The image pixel data is thus divided in to multiple clusters and per cluster the mean value is taken as part of feature vector. At BTC level 1 only one threshold value is used to divide the pixel data to get two clusters and respective mean of these clusters as upper mean and lower mean are computed, resulting in to feature vector of size six (two value per colour plane). In next level each cluster can be further divided into two parts with respect to its mean value resulting into total four clusters per colour plane to get feature vector of size twelve (four per plane). Thus, BTC can be extended to multiple levels to get BTC Level 2, BTC Level 3, etc. [39] and [40] proposed an extension of CBIR techniques based on multilevel BTC using nine sundry colour spaces. The performance of this technique increases gradually with increase in level up to certain (Level 3) and then increases slightly due to voids being created at higher levels. In all levels of BTC Kekre's LUV color space gives best performance.

In most of the BTC approach existed in literature, the technique was used for classification photographic images human being, animals, and natural scenery. Moreover, this

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approach is used for image retrieval [45, 46, 47]. The relatively very few studies have been conducted so far related to RSI classification using BTC approach. Thus, there is a scope for further improvement in the existing algorithm for successful image classification based on BTC approach.

IV. CLASSIFICATION ACCURACY ASSESSMENT

The results of any classification process applied to RSI classification must be quantitatively assessed in order to determine their accuracy. As suggested by Lillesand and Kiefer [17], a classification process is not complete until its accuracy is assessed. The purpose of quantitative accuracy assessment is the identification of the sources of errors [48]. It is commonly assumed that the difference between an image classification output and the reference data is due to the classification error. A classification accuracy assessment generally includes three basic components: sampling design, response design, and estimation and analysis procedures [49]. Selection of a suitable sampling strategy is a critical step. The major components of a sampling strategy include sampling unit (pixels or polygons), sampling design, and sample size [50]. Possible sampling designs include random, stratified random, systematic, double, and cluster sampling.

A detailed description of sampling techniques can be found in [51]. The error matrix approach is the one most widely used in accuracy assessment [16]. One must consider the factors, namely reference data collection, classification scheme, sampling scheme, spatial autocorrelation, sample size and sample unit, in order to properly generate an error matrix. After generation of an error matrix, other important accuracy assessment elements, such as overall accuracy, omission error, commission error, and kappa coefficient, can be derived. These elements have very well defined with computation methods in the literatures [16, 52, 51, 53, 10].

The Kappa coefficient is a measure of overall statistical agreement of an error matrix, which takes non-diagonal elements into account. Kappa is usually attributed to [54,] but Kappa has been derived independently by others and citations go back many years [55]. It became popularized in the field of remote sensing and map comparison by [56]. In particular [51] state that “Kappa analysis has become a standard component of most every accuracy assessment and is considered a required component of most image analysis software packages that include accuracy assessment procedures.” Kappa analysis is recognized as a powerful method for analysing a single error matrix and for comparing the differences between various error matrices [56, 52, 24]. [56] studied number of evaluation methods of accuracy assessment and concluded that the methods based on confusion matrices and the K_{hat} statistical analysis are the most suited. Modified kappa coefficient and tau coefficient have been considered as improved measures of classification accuracy [57, 53]. Moreover, accuracy assessment based on a normalized error matrix has been conducted, which is regarded as a better presentation than the conventional error matrix [58, 59].

V. CONCLUSIONS

Developing computationally efficient algorithms for image classification without compromising the classification accuracy is of primary importance. Very few of existing classification algorithms has proved good precision in classifying RSI. Apart from this, the applicability of existing classifiers is very limited for classification of RSI of natural resources (land, water, and vegetation). In existing algorithms, all pixel data of image are used as feature vector for extracting the information from image, but the threshold values of pixels based on BTC, can be used for better performance. Based on the research gap, there is a scope for improvement in the existing RSI algorithms based on BTC approach and further development of efficient CBRSI algorithms

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