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Supervised Techniques and Approaches for Satellite Image Classification

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ABSTRACT

Remote Sensing is a multi-disciplinary technique for image acquisition and measurement of information. Remote sensing analysis paved way for satellite image classification which facilitates the image interpretation of large amount of data. Satellite Images covers large geographical span and results in the exploitation of huge information which includes classifying into different sectors. Different classification algorithms exist for image classification, but with the wide range of applications an algorithm with improved performance in terms of accuracy is required. Here in this paper we analyze different methods of supervised classification, different post classification techniques, spectral contextual classification and provide a comparative study on their efficiency.

Keywords

Classification, Supervised classifiers, Contextual classification, Cellular Automata

1. INTRODUCTION

Remote Sensing [1] is a technique introduced in early 1960's for data analysis and interpretation. Remote sensing collects huge amount of satellite data. Satellite remote sensing imagery covers large geographical area with high temporal frequency as compared to other imagery. Interpretation of these satellite images helps in a variety of applications as environmental conservation and management, water resource research, soil quality studies, environmental study after natural disasters, meteorology simulations, deriving land use and land cover information, preventing natural disasters, studying climatic change evolution.

Different techniques are used for data extraction from remote sensing images. Classification technique is the most useful technique for image interpretation and information extraction. Satellite image classification groups together the pixels of the image into number of different defined classes. The pixels are grouped together based on the digital values extracted from the satellite images. The pixel values extracted from the satellite images could be a single value as in case of gray scale image or multivariate value for multi spectral, temporal or multi-modal image [2]. The classification helps in extracting the information contained in different bands [3] of the satellite sensor and the information is extracted in terms of digital numbers which is then converted to a category.

Traditionally the method of classification can be supervised or unsupervised. The unsupervised classification [4] also referred to as clustering attempts for an unclear grouping when no sample sets are available. Supervised classification [5] requires input from analyst and identifies different classes based on the sample training sets. Supervised classification is more advantageous over unsupervised classification in most of the applications. A wide range of classical classification algorithms and different classifying methods exists for supervised classification. This paper provides a comparative analysis on the accuracy of different supervised classification algorithms and techniques.

2. LITERATURE SURVEY

Some of the frequent researches on different supervised classification methods for satellite images are discussed in the survey and a comparative analysis is done. Satellite Image classification has different approaches. Classical algorithms as parallelepiped[5][6], minimum distance[5][6], maximum likelihood[5][6], non-parametric classifiers and machine learning techniques as decision tree method[6] , support vector machine [4], Artificial neural networks[5] and genetic algorithms[5] which refines the learning process, were employed for efficient Image classification. All these methods have their strengths and limitations. Listed below are few problems related to one or the other of classical classification algorithms

(1) In some algorithms which classify the input image with high degree of heterogeneity, the pixels may be uncertain, i.e. a pixel can belong to more than one class
(2) Some other algorithm may misclassify a pixel
(3) Some may leave tiny areas of the image unclassified

3. SUPERVISED CLASSIFIERS

3.1 Parallelepiped classification

Parallelepiped classification [7] is a simple classification based on a decision rule for multispectral data. Decision boundaries for the parallelepiped algorithm are formed based on a standard deviation threshold which is chosen from the mean of each selected class in the training set. The decision boundaries form an interval between two pixel values with a hyper rectangle region in feature space. .A pixel is classified based on whether the value of that pixel lies above the lower threshold value and below the higher threshold value of the interval.

The mean value Mt of all the pixels for a class C for band M is taken for all the N classes of the training set and the variation (standard deviation) of the training data class C of band M of all the N classes be St. The mean and the standard deviation forms the parallelepiped boxes as decision boundaries or intervals for assigning the pixels. A pixel will be assigned to a particular class if the digital value Dv of the pixel lie inside the parallelepiped decision boundaries.

$$Mt - St \leq Dv < Mt + St \tag{1}$$

The pixel will be assigned to the class if its value lies in between the lower and the upper threshold value.

3.2 Minimum Distance Classifier

This is also a simple supervised classifier which uses the center point (average of all pixels of sample class) to represent a class in training set. This technique uses the distance measure, where the Euclidean distance is considered between the pixel values and the centroid value of the sample class. The pixel with the shortest distance with the class is assigned with that class.

The classifier is fast in execution, computation time is minimum as it depends mainly on the training dataset and all pixels will be classified, but the algorithm may be prone to errors resulting in misclassification of pixels as it will classify a pixel even if the shortest distance is far away. Spectral distance is calculated for all values of a class mean, the unclassified pixel is assigned to the class with the lowest spectral distance resulting in classification of all pixels.

The minimum distance algorithm is based on the minimum distance from the mean value Mt of each class of the training data to the digital value Dv of each pixel in the imagery. The minimum distance is calculated by using the Euclidean distance measurement.

$$sqrt(Dv - Mt)^2 \tag{2}$$

The class mean with the minimum distance with the pixel will be assigned as the class of the pixel.

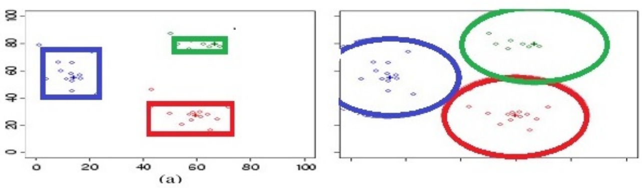

Fig. 1. Parallelepiped and Minimum distance Classification

3.3 Maximum Likelihood Classification

This method of classification calculates the probability for a given pixel to each class and then the pixel will be allocated to a particular class with the highest probability. It calculates the mean and covariance matrix for the training samples and assumes that the pixel values are normally distributed. A class can be characterized by the mean value and the covariance matrix. A probability density function is defined and the input pixels are mapped based on the likelihood that the pixel belongs to that particular class. The likelihood expressed for normal distribution can be calculated as below

$$L_k(X) = \frac{1}{2\Pi^{\frac{n}{2}}|\Sigma_k|^{\frac{1}{2}}} exp - \frac{1}{2}(X - m_k)\Sigma_k^{-1}(X - m_k)^t \tag{3}$$

Here X indicates the image data of n bands. $L_k(X)$ represents the likelihood of X belonging to class k, m_k is the mean vector of class k, Σ_k is the variance covariance matrix of class k.

This classifier is a sophisticated classifier with good separation of classes, but the training set should be strong to sufficiently describe mean and covariance structure. Also the algorithm is computationally intensive.

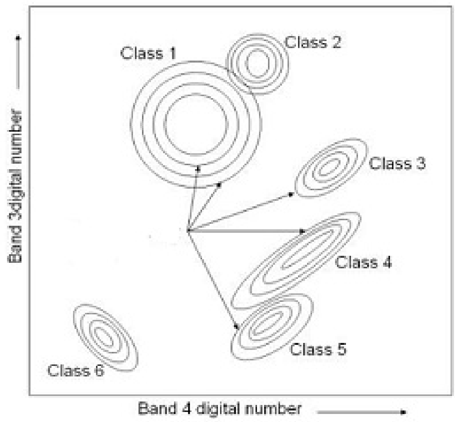

Fig. 2. Maximum Likelihood Classification

3.4 Decision Tree Method

In this method of classification a tree structure is built with root node and leaf nodes. The leaf nodes represent the classes of the features. Every interior node in the tree consists of a decision criterion. The attributes are partitioned based on spectral characteristics. The partition takes place based on the homogeneity (similarity of pixel values) until a leaf node is assigned with a particular class. A group of pixel values will be classified into two groups based on the separability with respect to a feature. This method uses the hierarchical rule and use Non-Parametric approach.

This method does not require any extensive design or training. Computational efficiency is good but requires complex calculations and the accuracy may depend fully on the design and selection of features.

3.5 Support Vector Machines

SVM classifier is based on decision planes that define decision boundaries. It builds a hyperplane from the training data which separates pixels with different class membership. The hyperplane gives the largest minimum distance to the training samples. Larger the margin, lower will be the generalization error.The method gives

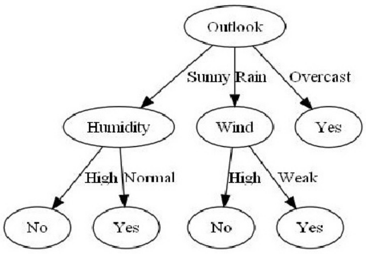

Fig. 3. Sample Decision Tree Method

a good separation achieved by the hyperplane. Here the computational complexity is reduced but training is time consuming as selection of optimum hyperplane is necessary for improved classification. Structure of SVM is difficult to understand. The performance and the accuracy of SVM depends on the hyperplane selection and the number of classes.

The hyperplane is normally represented by a normal vector v and a bias b, b an element in real numbers, v is an element of the feature space.

$$\boldsymbol{v.x + b = 0} \tag{4}$$

Here x corresponds to the digital values. SVMs usually maximizes the margin between data values of opposite classes.

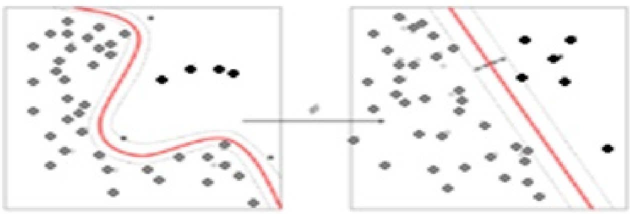

Fig. 4. Support vector machine

3.6 K-nearest neighbor algorithm

This is a non-parametric mining technique which uses K nearest [8] training samples to determine the pixel class. Here the K samples are chosen based on a similarity measure. Commonly used similarity measure is the distance function. The classification uses Euclidean, Manhattan or other distance measure to calculate the distance between a pixel and the different training samples. A class is assigned to a pixel based on the majority voting from the K training samples which would be to assign the most common class among the training samples. The technique is simple to process, but computationally expensive to select K nearest neighbors when the training dataset is large.

$$\boldsymbol{Euclideandistance = \sqrt{(Dv - Mt)^2}} \tag{5}$$

$$\boldsymbol{Manhattandistance = |Dv - Mt|} \tag{6}$$

Here Mt measures the digital value of each training sample and Dv represents the digital value of each pixel in the imagery

3.7 Artificial Neural Network Approach

The algorithms with artificial neural network approach simulate the human learning process for assigning meaningful labels to images. ANN imitates few functions of a persons mind. It consists of a sequence of layers with a set of neurons in each layer and the preceding and succeeding layers are joined by weighted connections. The accuracy and performance of artificial neural network highly depend on the network structure. ANN networks are data driven and self adaptive technique. The computation rate is high and handles noisy input. But ANN training is time taking and the network type architecture is difficult to choose. The papers [9] [10] discuss the satellite image classification using neural network approach and different classification algorithms. Per the research ANN has high classification accuracy rate but the time taken for training the classifier is huge. The approach is suitable for applications where study of dynamic data is needed as they have the capability to model nonlinear processes [11] and to identify unknown patterns and images based on their learning model.

3.8 Genetic Algorithm Approach

GA approach [12] is a search heuristic that mimics the process of natural evolution. It generates useful solutions to optimization and search problems using techniques inspired by natural evolution. Genetic algorithm based approaches are used for land cover classification[13] and an advantage of using the method is that it extracts classification rules that are easy for users to realize. GAs are techniques for optimization and finds the minimum or maximum of some arbitrary function. Paper [14] represents a model using the GA approach to extract classification rules for land use classification predictions in remote sensing imagery.

The weakness of a GA based classifier is time consumption when the training dataset contains large instances.

4. COMPARISON OF DIFFERENT SUPERVISED CLASSIFICATION ALGORITHMS

Comparison of Different classification methods are shown in Table 1 -Summarized comparison between different classification algorithms.

5. POST CLASSIFICATION OF SATELLITE IMAGES

The short comings of classification algorithms can be eliminated by applying the post classification techniques. The techniques of post classification improve the accuracy of the classified image.

5.1 Comparing Different Post classification Techniques

The problems related to classical classification algorithms like unclassified or misclassified pixels led to the application of post classification algorithms/techniques. Commonly used post classification techniques are Majority filter and probability label relaxation technique [15]. Here we discuss the accuracy comparison of different post classification technique with the technique of cellular automata

Table 1. Summarized comparison between different classification algorithms

Algorithm	Advantages	Disadvantages
Parallelepiped	• Fast Execution • Computationally Efficient	• Pixels not classified • Pixels in several classes
Minimum distance	• All Pixels classified • Fast Execution	Prone to commission errors
Maximum Likelihood	Provides good separation between classes	• Requires well trained training set • Computationally intensive
Decision tree method	• No extensive design and training • Reduced Computational time	• Complex calculation • Accuracy depends fully on feature selection
Support Vector Machine	Reduced Computational complexity	• Training is time consuming • Structure is difficult to understand • Accuracy may depend on the number of classes
K Nearest Neighbor Classifier	Low cost and effort for learning process	• Computationally expensive to find the K neighbors when sample dataset is large • Performance depends on the number of dimensions
Artificial Neural network	• Handles noisy input • Self adaptive technique	• Training is time taking • Difficult to handle network type architecture
Genetic Algorithmic approach	Extracts rules that are easier to realize	Time consumption is large for large training instances

5.2 Majority Filter

This technique of post classification relabels the center pixel when it is not a member of the majority class. The method improves the overall accuracy of classification but merges some land covers together. If p is the center pixel, then the pixel would be relabeled as

$$If(c_i > c_j \text{ and } c_i > c_t) \text{ then } p \text{ is assigned the class of } w_i$$

Here c_i and c_j refers to the count of pixels belonging to class i and j.

5.3 Probability Label Relaxation

This is an iterative technique which considers the probabilities of the neighboring pixels for updating the probability of the center pixel. The method is based on relation among pixel labels specified by compatibility coefficients describing the context of the neighbor.

The PLR method of post classification provides higher accuracy than the majority filter method, but it requires lot of computation and a wise choice of the compatibility coefficient.

5.4 Cellular Automata approach

The approach of cellular automata [16][17] consists of regular grid of cells. Each cell is associated with a particular state from a set of possible states. The state depends on the states of the neighboring pixels/cells and a set of rules. A Pixel changes its state based on a transition function and a set of rules.

The Post classification based on cellular automata reassigns a class of the pixel based on the class of the neighboring pixels based on defined rules and function

On comparing different post classification techniques, the cellular automata approach provides a better accuracy than other two filters

6. CONTEXTUAL CLASSIFICATION APPROACHES

6.1 Spectral and contextual classification

Common classification methods use the spectral properties of the satellite image pixels and the use of supervised or unsupervised algorithm depends on the analysts knowledge about the area under study.

The above defined techniques of classification works well if the images are non-noisy and the spectral properties define the classes sufficiently well. If wide variation in class pixel properties are present or in case of noisy image the image classification may not be correct and there would be small pixels that are not classified. To avoid this misclassification we have different techniques applied as contextual information [18] in addition to spectral data. Contextual algorithms uses mean values, variances, texture description from a pixel neighborhood to improve the pixel spectral classification. The methods usually reduce the error rates considerable as compared to non-contextual rules [19].The uncertainty of classes arising in the contextual method can very well used as information for indicating border zones.

6.2 Contextual classification through texture extraction

Texture describes the placement and spatial arrangements of repetition of tones and quantifies the variability of pixels in a neighborhood. The texture metrics can improve the classification accuracy through mitigating spectral confusion among spectrally similar classes. Texture can be considered the key visual criterion [20] for the information from imagery for forest and vegetation applications. One limitation of texture extraction is the existence of unreliable classification results near the edges of classes. In the paper [21] a characterization of the texture of images by using cellular automata approach has been explained.

6.3 Contextual classification based on spectral values

The spectral classifiers are the dominant approach for classifying remote sensing imagery due to their conceptual simplicity and easy implementation. The contextual information compliments the spectral classifiers. High resolution images are having higher within-class spectral variability [22]. Classification for images with high spectral variability provides less satisfactory results. The contextual information can address such problems and can attain better results.

7. RECOMMENDED APPROACH OF CELLULAR AUTOMATA WITH SPECTRAL AND CONTEXTUAL CLASSIFICATION

Different classification methods analyzed in the paper has its significance in different applications.A satellite image classification technique using the classical classification algorithm and applying an efficient post classification process as cellular automata approach with contextual classification which helps in eliminating the problems related to the traditional classification algorithm can provide an improved accuracy for classification. A method based on parallelepiped and minimum distance classifiers which undergoes a spectral classification followed by a contextual classification with a cellular automata approach of the image pixels can be an efficient method for accurate satellite image classification.. The approach can provide a better classification accuracy for satellite images with high degree of heterogeneity. The classical classification algorithms fails in case of classifying images with diversified characteristics as in case of green houses[23][24].

The uncertain and misclassified pixels disappear as contextual classification is applied based on neighborhood states if the pixel belongs to several class. Different problems related to the classical classification algorithm we discussed here would be eliminated by the use of contextual classification. The technique also provides a hierarchical classification based on the degree of membership of each pixel to a class. The post classification process of the ACA approach leads to uncertain pixel refinement.

8. EXPERIMENTAL ANALYSIS

The experimental analysis of the proposed approach of applying cellular automata and contextual post classification[ACA] to classical classification algorithms showed a more efficient system in terms of accuracy. The ACA approach applied to the classical parallelepiped algorithm showed an increase of 4.8% for low classification complexity field images and 15.7% for high classification complexity images. The classification complexity of images is considered based on the heterogeneity of images.For the minimum distance algorithm the ACA modification led to an increase of 3.3% for low complexity images and 9.7% for high complexity images[25].

The Table 2 shows a comparative analysis of different classification algorithms with the ACA approach in terms of accuracy.

Table 2. Experimental Analysis of Proposed ACA Approach

Algorithm	Low Complexity Field Images	High Complexity field images
ACA Parallelepiped	89.15%	82.01%
ACA Minimum Distance	88.36%	78.87%
Naive Bayes	87.87%	72.57%
K-NN	85.95%	71.20%

9. CONCLUSION

This paper analyses different supervised classification approaches and methods, post classification algorithms and the concept of applying cellular automata and contextual classification for satellite image classification. Satellite image classification is a field which has great significance for different socio-economic, environmental applications. Through classification of satellite imagery, the information as cadastral information, land cover type, vegetation type, soil properties could be obtained. Different methods discussed in the literature review emphasize on different techniques and has its own advantages and limitations. But they can be used for different specific applications. The classical classification algorithms with other learning techniques were discussed. The researches specifying different post classification techniques were also discussed.The role of contextual classification in addition to spectral classification and its significance for classifying images with high degree of heterogeneity were also analyzed.

The comparative study concluded with the high accuracy rate of classification for the method of classical classification algorithm combined with cellular automata with contextual classification which combines the classification and post classification techniques.

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