

An Efficient Satellite Image Classification Method Using Cellular Automata

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Abstract- Remote Sensing is a multi-disciplinary technique for image acquisition and exploitation. A major goal of remote sensing is data analysis and interpretation. 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 classifying satellite images but for variety of applications a classification technique with improved performance in terms of accuracy is required. Classification based on cellular automata offers many advantages that improve the result of classical classification algorithms. The concept groups together classification and post-classification processes for producing a highly accurate classified image. The proposed paper performs spectral and contextual classification incorporating fuzzy rules and states for attaining improved accuracy and can configure a personalized land use classification. The system improves the satellite image classification accuracy by applying fuzzy rules which is used for eliminating the uncertain pixels obtained when applying the spectral and contextual classification. The resultant classified image will be an image with improved accuracy.

Index Terms— Classification, Supervised classifiers, Contextual Classification, Cellular Automata, Fuzzy Classification

I. 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 [2] 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 [3]. The classification helps in extracting the information contained in different bands [4] of the satellite sensor and the information is extracted in terms of digital numbers which is then converted to a category. 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 also referred to as clustering attempts for an unclear grouping when no sample sets are available. Supervised classification 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.

II. LITERATURE REVIEW

Few of the classical supervised classification methods for satellite images are discussed. 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, Artificial neural networks and genetic algorithms 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.

- a) 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.

- b) Some other algorithm may misclassify a pixel
- c) Some may leave tiny areas of the image unclassified.
- d) High computational complexity and training time.

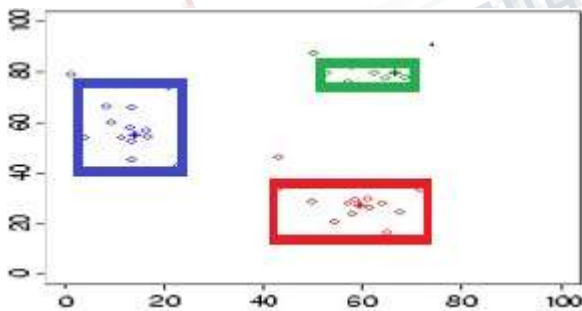
The classical classification parallelepiped algorithm is a simple classification based on a decision rule for multispectral data. Decision boundaries for the parallelepiped algorithm are formed based on a standard deviation threshold which is chosen from the mean of each selected class in the training 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 parallelepiped classifier [7] is fast but with less accuracy as the pixel values may be overlapped with different class boundaries as some parallelepipeds overlap. This classification also results in unclassified pixel values as some pixel values may lay outside all the decision boundaries.

The mean value M_t 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 S_t . 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 D_v of the pixel lie inside the parallelepiped decision boundaries.

$$M_t - S_t \leq D_v < M_t + S_t$$

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



Parallelepiped classification

Another classical algorithm minimum distance classifier 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

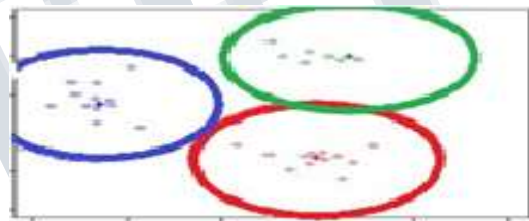
of the sample class. The pixel with the shortest distance with the class is assigned with that class.

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 M_t of each class of the training data to the digital value D_v of each pixel in the imagery. The minimum distance is calculated by using the Euclidean distance measurement.

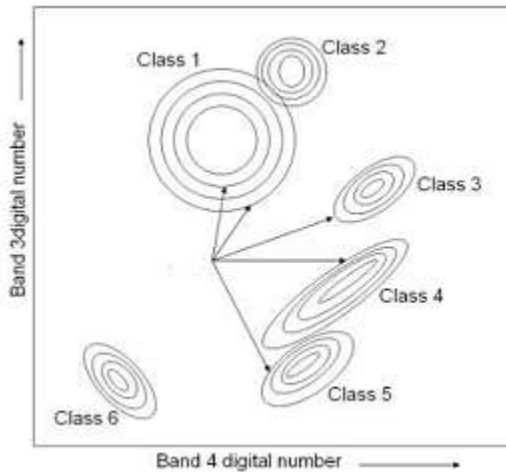
$$\sqrt{(D_v - M_t)^2}$$

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



Minimum Distance Classification

The maximum likelihood classification algorithm 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.



Maximum Likelihood Classification

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.

The shortcomings of classification algorithms like unclassified or misclassified pixels can be eliminated by applying the post classification techniques. The techniques of post classification improve the accuracy of the classified image. Different techniques of post classification exist like the majority filter which improves the overall accuracy of classification but merges land covers together and the probability label relaxation[8] method which considers the probabilities of the neighboring pixels for updating the probability of the center pixel. The PLR method of post classification requires a lot of computation.

Cellular Automata[9] is another approach of post classification which consists of a 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. This approach of post classification provides better accuracy with less computation.

The above defined techniques of classification work 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 a noisy image the image classification may not be correct and there would be small pixels that are not classified. Contextual techniques[10] can be applied along with the spectral characteristics for eliminating such issues.

The spectral classifiers are the dominant approach for classifying remote sensing imagery due to their conceptual simplicity and easy implementation. The

contextual information complements the spectral classifiers. High resolution images are having higher within class spectral variability. Classification for images with high spectral variability provides less satisfactory results. The contextual information can address such problems and can attain better results.

III. PROPOSED METHOD

The proposed system presents a new methodology for classifying the image pixels based on both spectral and contextual data of each pixel and the concept of cellular automata. The three main objectives of the methodology are:

- To improve the accuracy rate of Classical classification algorithms as parallelepiped and minimum distance supervised algorithms by means of contextual information to avoid misclassification of the uncertain or noisy pixels. The algorithm must classify the problematic pixels, taking into account not only their spectral data (ambiguous for uncertain pixels, wrong for noisy pixels) but also their neighbours contextual data in order to improve the final classification accuracy rate.
- To obtain a hierarchical classification divided into layers of membership degree to each class. ACA must classify only the pixels which are at a maximum spectral distance in the featured space with respect to the corresponding class center.
- Get a detailed list of the uncertain and noisy pixels which could be useful in case of any failure in the classification process. A list of those edges that determine the spatial edge of the image classes is also obtained.

The cellular automata concept is based on the following associations with the basic elements.

- Each pixel of the satellite image corresponds to a particular cell of the cellular automata grid.
- Each different class of the classification process corresponds to a particular state of cellular automata.
- Each cell can have Von Neumann (4 surrounding pixels) neighborhood, Moore (8 surrounding pixels) neighborhood, Extended Moore (24 surrounding pixels) neighborhood to customize the final classification process.
- The results obtained by the classical supervised algorithms are improved when the transition function correctly identifies the class based on the features of the current cell and the neighborhood cells using mixed spectral and contextual data.

The basic idea of the approach is to apply the

spectral classification to the classical classification algorithms as parallelepiped or minimum distance algorithms considering a threshold for spectral distance for classification in each iteration. The spectrally classified pixels are then applied with contextual classification incorporating fuzzy rules and states.

ACA uses the following modified formula for parallelepiped algorithm

$$CV(A,n) - DR^{thr} \leq SV(x,n) \leq CV(A,n) + DR^{thr}$$

Here DR^{thr} is the dispersion range of class A in band n at iteration i of the classification process. The value of dispersion is increased in each iteration taking into account the thr value.

For the minimum distance algorithm, ACA uses the modified formula

$$CA_{j,class} = A|d_{j,A} \leq thr$$

The spectral classification requires the following parameter values as input

- The centroid and dispersion range of the training samples
- Number of classes
- The threshold value
- Spectral values of pixel to be classified

The behaviors of the classical algorithms were adjusted with the parameters of threshold and number of iterations. The spectral classification, in the first iterations assigns the pixels which are really close to the class. After the first iteration the image pixel that satisfy the threshold criterion changes the initial state of class from Φ to state 1 and all the satisfying spectral classes would be assigned to the pixel. The pixels that are assigned classes in the current iteration and changed the state would then proceed for contextual classification. After spectral classification of a pixel the states quality and type of the pixel would remain as Φ and would change its state in the contextual classification.

The output of spectral classification would be the classified pixels with the spectral classes assigned for that iteration and the quality of the pixel indicating at which iteration the pixel is classified.

The contextual classification applies the rules of cellular automation to the spectrally classified pixels. Here fuzzy rules are applied which is used for eliminating the uncertain pixels obtained when applying the spectral and contextual classification. Fuzzy rules assigns the pixel values to classes or states based on the value of a membership function. Here the membership degree would be based on the iteration at which the particular class is

assigned to the pixel. For uncertain pixels the spectral classification would be followed by application of fuzzy rules based on the membership degree of each pixel to a particular class. The pixel will be assigned to the class with which it is having higher membership degree. In case if the membership degree of the pixel to all the classes assigned falls in the same range, contextual classification is applied to assign the class for that particular pixel.

The membership degree of each pixel belonging to a particular class is calculated as

$$md_{x,A} = \frac{\text{iteration}_{A,finish} - \text{iteration}_{x,classified(A)}}{\text{iteration}_{A,finish}}$$

Here $md_{x,A}$ = membership degree of pixel x to class A

$\text{iteration}_{A,finish}$ = iteration in which all of the pixels of class A have been classified;

$\text{iteration}_{x,classified(A)}$ = iteration in which pixel x has been classified into class A.

IV. RULES DEFINED FOR CONTEXTUAL CLASSIFICATION ARE

1. For number of spectralClass as 0 because the current pixel has wrong spectral values: [class][quality][type] = majority class of the neighborhood, iteration, noisy.
2. For number of spectralClass as 1 and all of the neighborhood class states are emptyClass or the same as current pixel then: [class][quality][type] = spectralClass, iteration, focus.
3. For number of spectralClass as 1 and any neighborhood class state is different from current pixel class then: [class][quality][type] = spectralClass, iteration, edge. Rule #4 is the fuzzy rules for uncertain pixels which is based on the membership degree.
4. For number of spectralClass > 1 then: [class][quality][type] =
 - a) Spectral class with higher membership degree, iteration, uncertain : If membership degree of two classes are different
 - b) Majority class of the neighbourhood among the dubious classes, iteration, uncertain. If the membership degree of two classes are same

A. The system architecture is shown in Fig:3

Data Set: High Resolution satellite images were taken from Google Earth, Universal Map downloader. Images reflecting each class were used for obtaining the training values for classification making up the training dataset. Four different classes were defined specifying the land cover features.

Classification is done using three algorithms as Main Algorithm for cellular Automata, Spectral classification and contextual classification.

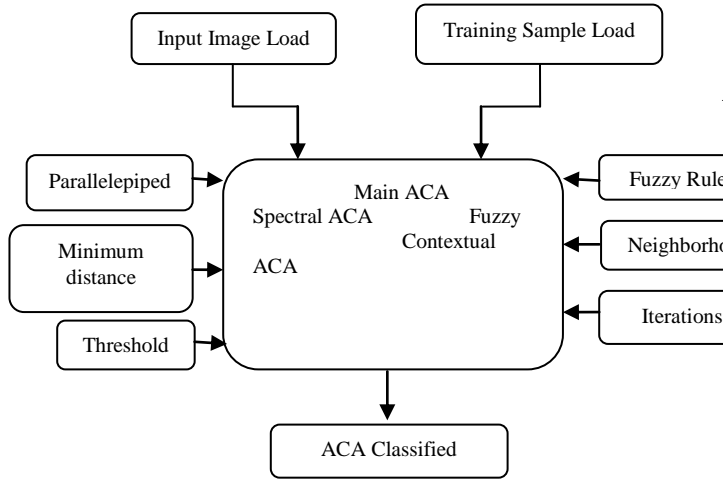


Fig: 3

B. Main ACA Algorithm Pseudocode

Input: Training sample, Input Image to be classified.
Output: Accurately classified Image.

CA.Q = {q_{class}, q_{quality}, q_{type}} Set of 3 states per each CA cell
Auxiliaries: SV – Spectral values of all the pixels in all the bands, CV – Centroid value of all the pixels in all the bands, DR – Dispersion Range of all the classes in all the bands, thr – threshold for all the classes in all the bands. CAIter – Number of iterations of CA. CAr – neighbourhood dimension of cellular automation. i=current iteration of the cellular automation

Step 1: For i= 1 to CAIter Repeat steps 2 to 7
Step2: For each CA.Q_j |j=1 to numpixels Repeat steps 3 to 6
Step3: If CA.Q_{j,CLASS} = Φ, then
Step4: CA.Q_j =spectralACA(SV_j,CV,DR,CA.Q_j,thr)
Step5: If CA.Q_{j,CLASS} ≠ Φ, then
Step6: CA.Q_j =contextualACA(CA.Q_j, CA.r, i)
Step7: thr=thr+inc
Step8:Return CA.Q

C. Spectral ACA Algorithm Pseudocode

Input: SV_j – Spectral value of pixel j in all the bands
CV – Centroid value of all the classes in all the bands
DR – Dispersion Range of all the classes in all the bands
thr – threshold for class membership in each iteration.
CA.Q_j = {q_{class}, q_{quality}, q_{type}} Set of 3 states of cell j
Output: CA.Q_j = {q_{class}, q_{quality}, q_{type}} Set of 3 states of cell j

D. Spectral ACA(SV_j,CV,DR,CA.Q_j,thr)

Step1: For each class_A | A ∈ {1...numclasses} Repeat steps 2 to 3
Step2: hierarchicalclass(SV_j,CV,DR,thr,class_A) ∈ thr
Step3:then CA.Q_{j,class} = CA.Q_{j,class} + class_A
Step4:Return CA.Q_j

E. Contextual ACA Algorithm Pseudocode

Input: i=current iteration of the cellular automation
r – neighbourhood dimension of cellular automation.
CA.Q_j = {q_{class}, q_{quality}, q_{type}} Set of 3 states of cell j
Output: CA.Q_j = {q_{class}, q_{quality}, q_{type}} Set of 3 states of cell j

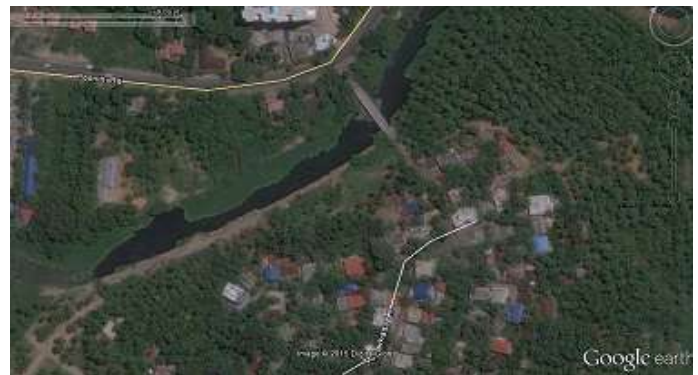
Contextual ACA(CA.Q_j, CA.r, i)

Step1: If Size(CA.Q_{j,Class}) = Φ, then
Step2: CA.Q_{j,Class} = majorityneighbourhood(j,CA.r)
CA.Q_{j,type} = “noisy”
Step3: If Size(CA.Q_{j,Class}) = 1 and
classEqual(CA.Q_{j,Class},CA.Q_{CA.r,class}) = True then
Step4: then CA.Q_{j,type} = “focus”
Step5: If Size(CA.Q_{j,Class}) = 1 and
classEqual(CA.Q_{j,Class},CA.Q_{CA.r,class}) = False then
Step6: then CA.Q_{j,type} = “Edge”
Step7: If Size(CA.Q_{j,Class}) > 1 then
Step8: Ifmembershipdegree(CA.Q_{j,Class}A)=
membershipdegree(CA.Q_{j,Class}B) then otherwise Step10
Step9: then CA.Q_{j,type} = “Uncertain”
CA.Q_{j,Class} = majorityneighbourhood(j,CA.r)
Step10: CA.Q_{j,Class} = classhighmembershipdegree(CA.Q_j)
Step11: CA.Q_{j,quality} = i
Step12: Return CA.Q_j

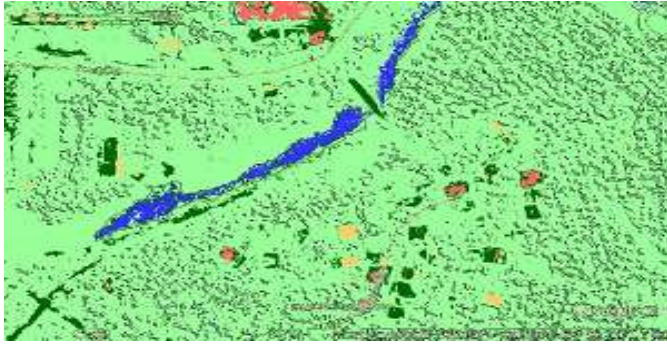
V. EXPERIMENTAL RESULTS

For the experiment a heterogenic Google Earth Image was used to classify the features into 1)Water Body (Blue) 2) Agriculture(Green) 3)Baresoil(Yellow) 4) Urban Area(Red).

The algorithm could successfully classify the Google Earth image giving an accurate classification.



Input Image



Output Classified Image

VI. CONCLUSION

The improved ACA method eliminates all the problems related to classical classification algorithm. All the unclassified pixels disappear as the dispersion range increases at each iteration until all the image pixels are classified. Uncertain pixels disappear using the Fuzzy rules and contextual techniques using neighborhood for pixels with several classes.

In addition to eliminating the problems related to classical classification algorithms, the system improves the accuracy of the algorithms by using contextual and cellular automata concept during the first iterations of classification, only pixels with strong spectral properties will be classified. As iteration increases only pixels with high diversity classes remains unclassified, then in further iterations ACA refines the process of classification until all of the pixels are classified. The ACA improvement of accuracy for low and moderate complexity satellite images are good and for high complexity it is excellent.

A hierarchical classification with layers based on the membership degree is also provided. the range of membership distance permitted with each class increases with every iteration.

A method of edge detection and the availability of the list of focus, edge, noisy and uncertain pixels is an added advantage as it is useful for later interpretation and analysis. The approach here assigns the uncertain pixels to the spectral class which has the higher membership to the class. The method is a type of soft classification unlike other hard classification methods where the decision is too rigid. It is characterized by a membership function implemented with if-then rules.

The Fuzzy classification scheme is designed for improving the accuracy of satellite image classification through spectral and contextual techniques together with the application of fuzzy rules for eliminating the uncertain pixels. High resolution satellite images provide classification with improved accuracy which can be used for land cover classification. This can further be applied for urban development, natural resource management and conservation, Different personalized study areas and many

different applications.

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