Satellite Image Classification With Ensemble Model Using Machine Learning

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Abstract- *Satellite image classification process involves grouping the image pixel values into meaningful categories. Several satellite image classification methods and techniques are available. In existing k-medoid clustering technique is used for clustering the satellite data, with this method not able to cluster accurately all the classes. In our proposed method self-organizing map as a clustering technique is used. Self-organizing maps learn to cluster data based on similarity,topology,with a preference of assigning the same number of instance to each class. Self-organing maps are used both to cluster data and to reduce the diamensionality of data. They are inspired by the sensory and motor mappings in the mammal brain, which also appear to automatically organizing information topologically. Ensemble classifiers meld results from many weak learners into one high-quality ensemble model. Our proposed technique is Ensemble clustering with subspace discriminant algorithm for classification of satellite data into water, Agriculture, Barren land, Green land. The proposed method of self-organing map clutering and ensemble classifier with subspace discriminant is given best result compared to existing ones.*

Keywords- Red,Green and Blue(RGB), Lightness, chrominance of red and green(LAB),Chrominance of yellow and blue,Self-Organizing Map(SOM), Expectation Maximization Algorithm(EM), Ensemble Subspace Discriminant Algorithm(ESDA).

I. INTRODUCTION

Identifying the physical aspect of the earth's surface (Land cover) as well as how we exploit the land (Land use) is a challenging problem in environment monitoring and many other subdomains. This can be done through field surveys or analyzing satellite images(Remote Sensing). While carrying out field surveys is more comprehensive and authoritative, it is an expensive project and mostly takes a long time to update.

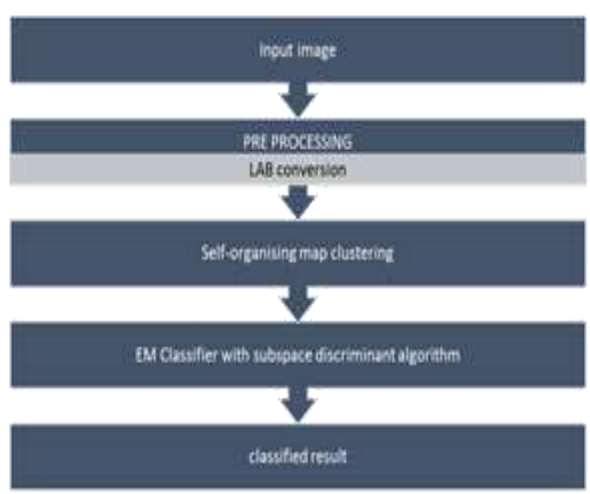
Supervised machine learning is the data mining ask of inferring a function from labeled training data. The training data consist of a set of training examples. It is a learning in which we teach or train the machine using data which is well labeled which means some data is already tagged exactly.Self-organizing maps uses neural networks that learn the topology and distribution of the data.

The Satellite image is given as the input to the system which is then processed in the pre-processing stage that converts the RGB image format into LAB converted form. The image is converted into LAB form to cluster the data easily.L – Lightness , A - Chrominance of Green and Red colours and B - Chrominance of Blue and Yellow colours.

In the segmentation phase, Self-Organizing map clustering is used. This is unsupervised form of clustering in neural networks and results with 4 classes namely Barren land, agricultural land, Water land and Green land. Ground truth is the pixel value that is taken from the image and comparing with the our proposed results to detect the accuracy of the results. Satellite image is vectorized into m*n*3 each of 250 pixels.

Vectorization refers to the changing of pixels in the image into single vector. The output matrix is of the form 187500*1 matrix. Input image is of a colour image with 512*512*3. Unsupervised type of learning is used here in this module.

Feature extraction phase is the extraction of colour for each for the 6 colours considered for our 4 classes. Ensemble subspace discriminate classifier is used to classify the segmented and clustered data using supervised learning.



II. RELATED WORK

This section we discuss various proposed architectures, we first wrap the original satellite image into multiple different scales. The images in each scale are employed to train a deep convolutional neural network.the multiscale satellite images are fed into their corresponding SPP-nets, respectively, to extract multiscale deep features. This paper presents a generalization of self-organizing maps with 1-D neighborhoods that can be effectively applied to complex cluster analysis problem.These features enable the network-working in a fully unsupervised way (I.e.,using unlabeled data without a predefined number of clusters)-to automatically generate collections of multiprototypes that are able to represent a broad range of clusters in data sets. A sensitivity analysis of our approach to changes in control parameters and a comparative analysis with an alternative approach are also performed. A new background modeling method called stacked Multi-layer Self-Organizing Map Backgound Model (SMSOM_BM) is proposed, which presents several merits such as strong representative ability for complex scenarios, easy to use and so on. More specifically,every pixel is modeled by a Stacked Multi-layer Self-Organizing Map (SMSOM),and spatial consistency is considered at each layer.This letter presents a method for satellite image classification aiming at the following two objective:

1) involving visual attention into the satellite image clasification.

2) Handling the satellite image classification without the learning phase.

The images are classified according to a newly defined

"image-to-category" similarity based on the coding Coefficients. The increased availability of high-Resolution synthetic aperture radar (SAR) satellite

Images has led to new civil application of these data.the vast range of SAR imaging parameters and the diversity of local targets impact the image product characteristics and need special care. This holds for typical remote sensing example such as coastal monitoring or the characterization of urban areas where we want to understand the transitions between individual land cover categories. Segmentation of satellite images using a novel adaptive non parametric mean-shift clustering algorithm is proposed in this paper. Image segmentation refers to the process of splitting up an image into its constituent object. It is also an important step in bridging the semantic gap between low level image interpretation and high level visual analysis.Extensive experiments on several multispectral satellite images have confirmed the effectivity of this proposed approach in comparison to some widely used state of the art segmentation methods.

III. PROPOSED SYSTEM

Self-Organizing maps learn to cluster data based on similarity, topology, with a preference of assigning the same number of instance to each class. Self-Organizing maps are used both to cluster data and to reduce the dimensionality of data. They are inspired by the sensory and motor mappings in expectation-maximization(EM) algorithm, which also appear to automatically organizing information topologically. Discriminant analysis is aclassification method. It assumes that different classes generate data based on different Gaussian distributions. Use random subspace ensemble(subspace) to improve the accuracy of discriminant analysis(classification Discriminant). Subspace ensembles also have the advantage of using less memory than ensembles with all predictors, and can handle missing values (NaNs).

V. IMAGE SYSTEMATIZATION

A. PRE-PROCESSING

In this module In pre-processing phase, RGB image is converted into LAB form(L for Lightness, A for chrominance of Green and Red colours and B for Chrominance of Blue and Yellow colours).

Input image is of a colour image with 512*512*3 represents the R, G, B colours. Satellite image is vectorized into m*n*3 each of 250 pixels. Vectorization refers to the changing of pixels in the image into single vector. The output matrix is of the form 187500*1 matrix. Output image is of LAB converted image 2*262144 after vectorization.

B. SEGMENTATION

The preprocessed image is given as input. Unsupervised type of learning is used in segmentation phase in neural network. Self-organizing map clustering is based on neural network and results with 4 classes. This splits up LAB converted image into vectors(pixels). It calculates Euclidean distance and weights based on vectors in neural network automatically. LAB conversion is mainly to cluster the data easily. Self-Organizing Map groups every pixels into the exact cluster it belongs to.

The goal of learning in the self-organizing map is to cause different parts of the network to respond similarly to certain input patterns.

An illustration of the training of a self-organizing map. The blue blob is the distribution of the training data, and the small white disc is the current training datum drawn from that distribution. At first (left) the SOM nodes are arbitrarily positioned in the data space. The node (highlighted in yellow) which is nearest to the training datum is selected. It is moved towards the training datum, as (to a lesser extent) are its neighbors on the grid. After many iterations the grid tends to approximate the data distribution (right).

The neuron whose weight vector is most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. The magnitude of the change decreases with time and with distance (within the lattice) from the BMU. The update formula for a neuron v with weight vector Wv(s) is

where s is the step index, t an index into the training sample, u is the index of the BMU for D(t), α(s) is a monotonically decreasing learning coefficient and D(t) is the input vector; Θ(u, v, s) is the neighbourhood function which gives the distance between the neuron u and the neuron v in step s.

Variables :

These are the variables needed, with vectors in bold,

- s is the current iteration
- λ is the iteration limit
- t is the index of the target input data vector in the input data set
- D(t) is a target input data vector
- υ is the index of the node in the map
- is the current weight vector of node
- u is the index of the best matching unit (BMU) in the map
- Θ(u,v,s) is a restraint due to distance from BMU, usually called the neighbourhood function, and
- α(s) is a learning restraint due to iteration progress.

Algorithm :

1. Randomize the node weight vectors in a map
2. Randomly pick an input vector
3. Traverse each node in the map

1. Use the Euclidean distance formula to find the similarity between the input vector and the map's node's weight vector
2. Track the node that produces the smallest distance (this node is the best matching unit, BMU)

4. Update the weight vectors of the nodes in the neighbourhood of the BMU (including the BMU itself) by pulling them closer to the input vector

5. Increase s and repeat from step 2 while s< λ

C. FEATURE EXTRACTION

Pixels are of the form 1, 2, 3 & 4 based on our classified classes. Parameters like mean, standard deviation, variance, skewness, kurtosis are used to find the accurate values mathematically.

Skewness , $S=E(x-\mu)^3\sigma^3$.

Kurtosis , $k=E(x-\mu)4\ \sigma4$.

Skewness is a measure of the asymmetry of the data around the sample mean. Kurtosis is a measure of how outlier-prone a distribution is. Normal distribution is 3.All the 6 colours namely R, G, B, L, A, B with 4 defined classes produces 24 features for a single cluster. For each of the 6 colour spaces the features are extracted and are stored. These data are then compared to the input image that is given to the system.

D. CLASSIFICATION

In this phase, Ensemble Subspace Discriminant Classifier is used. This classifier is used to classify the feature extracted output image. Classifier gives the output as a single image with color classified for 4 classes that are defined. The output image is of colored form which classifies the 4 classes. Gives the total percentage of each of the classes. Discriminant analysis is a classification method. It assumes that different classes generate data based on different Gaussian distributions.

Use random subspace ensembles (Subspace) to improve the accuracy of discriminant analysis (Classification Discriminaant). Subspace ensembles also have the advantage of using less memory than ensembles with all predictors, and can handle missing values (NaNs).

The basic random subspace algorithm uses these parameters.

- m is the number of dimensions (variables) to sample in each learner. Set m using the N Pred To Sample name-value pair.
- d is the number of dimensions in the data, which is the number of columns (predictors) in the data matrix X.
- n is the number of learners in the ensemble. Set n using the N Learn input.

The basic random subspace algorithm performs the following steps:

1. Choose without replacement a random set of m predictors from the d possible values.
2. Train a weak learner using just the m chosen predictors.
3. Repeat steps 1 and 2 until there are n weak learners.
4. Predict by taking an average of the score prediction of the weak learners, and classify the category with the highest average score.

VI. CONCLUSION

Hence, in this paper an HDP_IBPs model is proposed to address the problems of unsupervised classification in VHR panchromatic satellite images. Our contribution is to propose a nonparametric Bayesian classification algorithm by combining the HDP with the IBP to consider the hierarchical spatial information of satellite satellite images.On the one hand ,the model can be used to classify the panchromatic image automatically without the knowledge of the number of classes in an unsupervised way.On the other hand, the hierarchical spatial information is built in our model to make sure the spatial consistency of the classification results.However,it is also possible to apply the proposed model to multispectral satellite images by choosing a reasonable topic distribution (e.g., Gaussian distribution)instead of a multinomial distribution.In the future,we will extend the proposed model to analyze multispectral remote sensing images.

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