Crop Classification Using Multi-Spectral Satellite Images

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Abstract-*Information about the location and area of crop has significant economic and environmental applications. Remote sensing techniques have been developed to allow researchers to accurately classify large vegetation area at reduced cost. One of the most important uses is to solve the problem of crop classification, i.e., differentiating between various crop types. Satellite images are a reliable source for investigating the temporal changes in crop cultivated areas. In our project, a novel bat algorithm (BA)-based clustering approach can be used for crop type classification problems using a multispectral satellite image. The crops that are to be classified are paddy and sugarcane. The proposed BA partitional clustering algorithm is used to extract information in the form of optimal cluster centers from training samples. The extracted cluster centers are then validated on test samples. Thus, BA can be successfully applied to solve crop type classification problems.*

Keywords-Multispectral satellite image, Clustering, Bat Algorithm.

I. INTRODUCTION

Agriculture is the science or practice of producing and harvesting crops in a systematic manner. Increment in agricultural yield is now a necessity due to constrictions in the expansion of acreage and constantly increasing demand for food. The agricultural productivity is defined as the product of crop yield and planting area and hence production estimation consists of area prediction and yield estimation. Therefore, there is a strong need to make the optimum use of available resources for cultivation. Satellite images can also be a viable source for investigating the temporal changes in the agricultural activities of a particular area. The crop growth, from sowing through to harvesting, can be monitored using these satellite images. The ortho-rectified and geo referenced satellite images can be used to identify problematic areas and the size of the area affected. Seasonal changes and abnormalities in vegetation can also be determined. Additionally, they can also be used to make an early estimate of the crop yield. Further, based on the available information, activities like – deciding type of crop and its acreage, determining the growth stage of crop, delineating their extentcan be planned in advance. All such information can be used in the overall improvement of the agricultural yield.

Multi-spectral satellite images facilitate identification and classification of crops, since they take into consideration the changes in reflectance as a function of the particular crop type. Crop classification finds applications in auditing land usage, soil and water quality studies, and planning efficient crop cultivation. But due to the variability in cultivation of crops within a geographical area, the process of classification is a major challenge.

We propose a novel BA based clustering approach for solving crop type classification problems. The data sets used were divided into training and test samples. The proposed algorithm is a partitional supervised clustering where training samples are used to extract knowledge in the form of optimal cluster centers. The extracted cluster centers are validated on the test samples. Clustering techniques commonly use objective functions. This objective function when applied on the training data with a population-based algorithm can converge to the globally optimal cluster centers.

This paper is organized as follows. In Section 2 and 3, we discuss BA and its implementation to solve clustering problems with an illustrative example. Results are presented and discussed in Section 4. We conclude our work in Section 5 by summarizing the results.

II. METHODOLOGY

The BA is a new powerful nature-inspired meta-heuristic optimization algorithm which is based on the echolocation capability of the micro bats.

During the search process, BA uses a frequency tuning procedure to intensify the diversity of the solutions in the population. At the same instance, it uses automatic zooming to balance exploration and exploitation by mimicking the variations in the pulse emission rate and loudness of bats when searching for the pray. The BA has been developed with the following assumption.

1. All the bats make use of their echolocation ability to measure distance and they are able to differentiate between their prey and the background.
2. Bats fly arbitrarily with velocity vi at position xi, fixed frequency f and loudness A0 to detect their targets. Bats automatically adjust the wavelength (or frequency) of the pulses and its rate of pulse emission, depending on the vicinity of the target.
3. The loudness is assumed to vary from a very large positive value A0 to a minimum constant value Amin.

The position xi and velocity vi should be defined in a d-dimensional search space and is subsequently updated in successive iterations. The new solutions xit and vit are calculated for every iteration t as follows:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \quad (3)$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_*) f_i \quad (4)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (5)$$

Whereβ is an uniform random number between [0, 1], x* is the current global best solution which is obtained after comparing all the solutions among all the n bats. The velocity increment is given by a product of λifi. Hence depending on the domain of interest, one can use fi (or λi) to adjust the velocity change while keeping other factor λi (or fi) constant. For implementation f ∈ [0, 100] can be used depending on domain size of the interested problem.

After updating the positions of the bats, a random number is generated. If the random number generated is greater than the pulse emission rate ri, a new solution is generated around the current global best solution using a local random walk.

$$x_{new} = x_{old} + \varepsilon A^t \quad (6)$$

Where ε∈ [-1, 1] is a random number, At=<Ait> is the average loudness of all the bats in iteration t. The loudness Ai and rate of pulse emission ri are updated as the iterations proceed. The loudness decreases and rate of the pulse emission increases as the Bat moves towards its prey (optimal solution). For easy implementation, A0 = 1 and Amin = 0 can be used. Here A=0 indicates bat has found its prey and has temporarily stopped emitting the pulses. The rate of pulse emission is taken as r ∈ [0, 1], where 0 indicates no pulse emission and 1 indicates maximum rate of pulse emission. The loudness Ai and rate of pulse emission ri are updated, and the new solution will be accepted if the random number is less than Ai and f(xi)<f(x*). The loudness Ai and rate of pulse emission ri are updated as:

$$A_i^{t+1} = \alpha A_i^t \quad (7)$$

$$r_i^{t+1} = r_i^0 \times (1 - \exp(-\gamma \times t)) \quad (8)$$

Where α and γ are constants. For any 0<α<1 and 0<γ, we have

$$A_i^t \rightarrow 0,\ r_i^t \rightarrow r_i^0,\ \text{as}\ t \rightarrow \infty \quad (9)$$

For the ease of implementation, we use α=γ=0.9 in our simulations. The update of velocities and position in BA may share some similarity with Particle Swarm Optimization (PSO) as fi controls range and pace of movement of solutions.

The aim of clustering is to minimize the objective function, when given N patterns

$$M(k) = \sum_{k=1}^{K} \sum_{i \in c_k} (x_i - c_k) \quad (10)$$

where K is the number of clusters, ck (k=1,2,..,K) is the kth cluster center, and xi (i=1,2,..N) is the pattern belonging to the kth cluster. Clustering is the assignment of patterns in the data into clusters, such that patterns in one cluster are similar, based on a certain similarity measure. The most commonly used measure is the distance measure.

In our work, cluster centers are the decision variables which are obtained by minimizing the objective function for all the training set patterns in the d-dimensional search space. The objective function being minimized is given by (11)

$$F_i = \sum_{j=1}^{D_{TRAIN}} d\left(x_j - p_i^{CL_{known}(x_j)}\right) \quad 11)$$

Where i=1…K, DTRAIN is the number of samples in training dataset, CLKNOWN represents the instance to which xj belongs to, p is the data matrix for cluster i.

In this work, BA is used to minimize the objective function, given by (11), in order to obtain the optimal cluster centers (decision variables). The BA is applied on training samples of two datasets. The number of samples used for training is described in the next section. On the application of BA to training samples, knowledge in the form of optimal cluster centers are extracted. These obtained cluster centers are then validated on corresponding testing samples of both datasets.

Objective function $f(x) = (x_1, x_2, \ldots, x_d)^T$
Initialize bat population x_i $(i=1, \ldots, n)$ and velocity v_i
Define frequency f_i at x_i
Initialize loudness A_i and rate of pulse emission r_i
while (t<$max\_number\_of\_iterations$)
generate new solutions by using Eqs (3), (4) and (5).
if (rand>r_i)
select global best solution among all the existing solutions
generate solutions using local random walk, Eq (6)
end if
if (rand<A_i&$f(x_i)$<$f(x_*)$)
accept the new solutions
update the loudness A_i(Eq 7) and
rate of pulse emission r_i(Eq8)
end if
sort the bats according to their fitness values and select global best solution
end while

Figure 1: Pseudo code for Bat Algorithm

III. IMPLEMENTATION

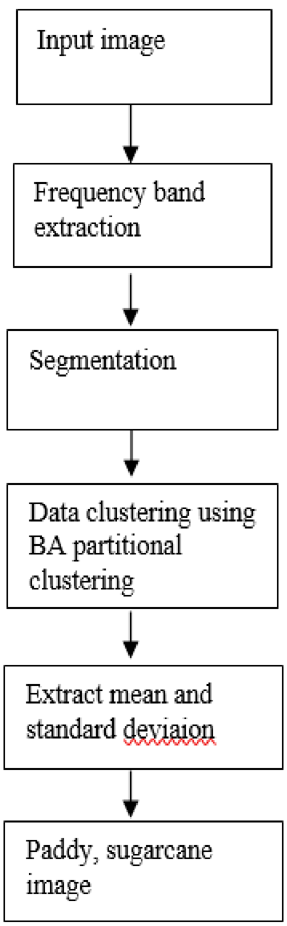

Figure 2: Block Diagram

IV. MODULE DESCRIPTION

4.1 Image Acquisition

Image acquisition is the action of retrieving an image from the source (m.earthobservatory.nasa.gov). The image that is acquired is completely unprocessed. Satellite images can also be a viable source for investigating the temporal changes in the agricultural activities of a particular area. The images are obtained from the region Tamil Nadu, India for the classification of crops namely paddy and sugarcane. From the given input image the crop growth from sowing to harvesting can be monitored. Seasonal changes and abnormalities in vegetation can also be determined. Multi-spectral satellite images facilitate identification and classification of crops, since they take into consideration the changes in reflectance as a function of particular crop type

4.2 Band Extraction

An input image is spatially sampled from hundreds of contiguous and narrow spectral bands, and correspondingly each pixel location is associated with hundreds of measurements, leading to a high-dimensional representation. Inevitably, the pixel values among different bands are highly redundant, which is due to the similar sensor responses in two adjacent bands. The objective of band clustering in our method is to find the highly correlated bands aiming to make the feature more discriminative.

With the help of the band extraction, the bands that shares the similar meanings are found. The relationship among the pixels of these data are further explored. Here we first group different bands into band clusters using K-means clustering, in which disjoint information is employed as the band distance measure.

Then the raw feature can be divided into T parts, given T as the number of band clustering. For the ith cluster, all the bands are regarded as the ith feature for each pixel, and the relevance among pixels is analyzed in each band cluster to carry out a graph-based learning in the next procedure, i.e., first-layer graph based learning.

4.3 Segmentation

In image segmentation, the different bands of the input image is partitioned into multiple segments (sets of pixels, also known as super pixels). The goal is to simplify the representation of an image into something that is more meaningful and easier to analyze. The objects and boundaries of the image are also located (lines, curves, etc.). A label is assigned to every pixel, that pixels with the same label share certain characteristics. Same as that, it is performed for all the bands that are extracted in the band extraction state.

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4.4 Mean and Standard Deviation

After the extraction of segmentation image, the mean and standard deviation values are then extracted for the process of data clustering.

$$\text{Mean } \bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} \qquad (1)$$

$$\text{StandardDeviation } \sigma = \sqrt{\frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \cdots + (x_n - \bar{x})^2}{n}} \qquad (2)$$

4.5 Data Clustering

The segmented image is obtained with the calculated values of the mean and standard deviation. Partitional clustering is carried out by dividing the data into a fixed number of clusters (which is known a priori), using a similarity measure. Bat Algorithm is used to minimize the objective function, in order to obtain the optimal cluster centers (decision variables). First, the optimal cluster is extracted. These obtained cluster center are then validated on corresponding testing samples. After clustering data, classification accuracy and time complexity are calculated.

V. EXPERIMENTAL RESULTS

5.1 Performance Evaluation

A Performance evaluation is that which determines an organization's behaviour and performance. It is the process of collecting, analysing or reporting information regarding the performance of an individual, group, organization, system or component. It can involve studying processes, strategies within organizations, or studying engineering processes, phenomena, to see whether output are in line with what was intended or should have been achieved. The input for the testing and training samples are generated based on the values of the mean and standard deviation. Totally 70 training samples and 30 testing samples are given for the classification.

- Correctly Classified Rate (CCR)

The percentage of cases Correctly Classified (CCR) is the most obvious accuracy measure. It is mainly for evaluate performance and accuracy of classifier. However, an impressive CCR is possible with very little effort.

Formula:

$$\text{CCR} = \frac{\text{CORRECTLY CLASSIFIED TESTED DATA}}{\text{TESTING DATA}}$$

$$= \frac{7}{10} \times 10$$

CCR = 0.70%

After classifying both testing and training images and getting output of correctly classified rate is 70%.

- Confusion Matrix

In the field of machine learning technique, a confusion matrix, also known as a contingency table or an error matrix. It is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. A table of confusion (sometimes also called a confusion matrix), is a table with two rows and two columns that reports the number of false positives, false negatives, true positives, and true negatives. This allows more detailed analysis than mere proportion of correct guesses (accuracy). Accuracy is not a reliable metric for the real performance of a classifier, because it will yield misleading results if the data set is unbalanced (that is, when the number of samples in different classes vary greatly).

	TRUE	FALSE
TRUE	21	9
FALSE	9	21

Figure 3: Confusion Matrix

Here, the confusion matrix to find its corresponding accuracy by classify the testing and training images and to calculate false positives, false negatives, true positives and true negatives.

- Accuracy

The accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's actual (true) value. The precision of a measurement system, also called reproducibility or repeatability, is the degree to which repeated measurements under unchanged conditions show the same results.

Accuracy = TP+TN/TP+TN+FP+FN

True Positive = 21   False Positive = 7

False Negative = 7 True Negative = 21

Accuracy = TP+TN/TP+TN+FP+FN

= 21+21/21+21+9+9 = 70%

VI. CONCLUSION

In this paper, the BA based clustering algorithm is proposed for solving crop type classification problems based on multi -spectral satellite imagery. The images are obtained from the Earth Observatory to demonstrate the robustness of the proposed approach. The performance of the proposed approach evaluated in terms of measure Classification Efficiency and Time Complexity.

The obtained results may indicate that BA can also be used to classify other types of data sets. Therefore, it may be useful to extend the proposed approach to solve a diverse range of classification problems, which can form a topic for further research.

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