International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, Volume 2, Issue 7, July 2012)

Remote Image Classification Using Particle Swarm Optimization

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***Abstract*— In order to have clarity in the satellite images we have used Particle Swarm Optimization technique. When incorporated with traditional clustering algorithms, problems such as local optima and sensitivity to initialization, are reduced, thus exploring a greater area using global search. This segmented image is further classified using Kappa coefficient.**

***Keywords*— Particle Swarm Optimization(PSO), Swarm Intelligence,Unsupervised learning, Remote Sensing, Clustering, Image Classification**

I. INTRODUCTION

Swarm intelligence (SI) is artificial intelligence based on the collective behavior of decentralized, self-organized systems. SI systems are typically made up of a population of simple agents interacting locally with one another and with their environment. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local interactions between such agents lead to the emergence of complex global behavior. Natural examples of SI include ant colonies, bird flocking animal herding, bacterial growth and fish schooling. Swarm Intelligence techniques include-Particle swarm optimization, Ant Code Optimization, Biogeography based optimization, Bee Colony Optimization, Stochastic Diffusion Search, Bacterial foraging optimization.

II. OBJECTIVES

The objective of this paper is to enhance the quality of the satellite image by placing the pixel into it's most appropriate land cover using particle swarm optimization. The main objective of using PSO is its easy understandability, with the use of simple mathematical calculations dealing with changing velocity and position.

III. PARTICLE SWARM OPTIMIZATION

This paper concentrates on a population based optimization technique, a field of Swarm Intelligence, called Particle Swarm Optimization[9]. Particle Swarm Optimization[9] is modeled after the social behavior of flocks of birds. This algorithm is initialized with a population of random solutions, called particles. Each particle flies through the searching space with a velocity that is dynamically adjusted. These dynamical adjustments are based on the historical behaviors of itself and other particles in the population.

$X_i = (x_{i1},x_{i2},\ldots\ldots\ldots\ldots,x_{iD})$,represents the ith particle, the best solution is $P_i = (p_{i1},p_{i2},\ldots,p_{iD})$, also called p_{besti}. The best solution of all particles is p_{gg} , also called $g_{best,}$ $V_i = (v_{i1},v_{i2},\ldots\ldots v_{iD})$ is the velocity of particle i. For every generation, the velocity changes according to the following equation:

$$v_{id} = w*v_{id} + c_1 * \text{rand}_1 ()*(p_{id} - x_{id}) + c_2 * \text{rand}_2 ()*(p_{gd}-x_{id})$$

$$x_{id} = x_{id} + v_{id}$$

Where d=1,2,…S, w is the inertia weight, it is a positive linear function of time changing according to generation iteration, often changing from 0.9 to 0.2. Suitable selection of inertia weight provides a balance between global and local exploration and results in fewer iterations. The acceleration constants, c_1 and c_2 represents the weighting positions. rand_1 and rand_2 are random functions which change between 0 and 1.

IV. REMOTE SENSING

GIS and remote sensing (Fakhruddin and Munir, 2007) are very useful in the formulating and implementation of the spatial and temporal changes which are essential component of regional planning to ensure the sustainable development. GIS and remote sensing techniques are quite developed and operational. Thus, Remote Sensing (Lillesand and Ralph, 1999) is the science (and to some extent, art) of acquiring information about the earth's surface without actually being

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in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information. the growth patterns of urban sprawl such as, the linear growth and radial, growth patterns.

One of the most effective ways to assess land use and land cover is through the use of remote sensing imagery collection from satellites and aircrafts. Remote sensing satellites (Fakhruddin and Munir, 2007) orbits at hundreds of miles above the earth continually imaging the surface and transmitting the images back to the ground station for use by the research community. This technology is an excellent medium for monitoring the condition of land throughout the globe.

V. PSO BASED REMOTE IMAGE CLASSIFICATION

There are spectral signatures set from seven bands. This data set (999 pixels) provided by the experts in the form of digital numbers (intensity value pixel in a digital image) which were taken with help of Eradas. These sets are taken by carefully selecting the areas (pixel by pixel) from all the images and noting the DN values of the pixels. From these DN values the rules are extracted by using the PSO algorithm. These rules are used for classifying the image in 5 classes: barren, rocky, urban, vegetation, waterbody. Approach use for classification of LISS III EOS image, the algorithm as follows

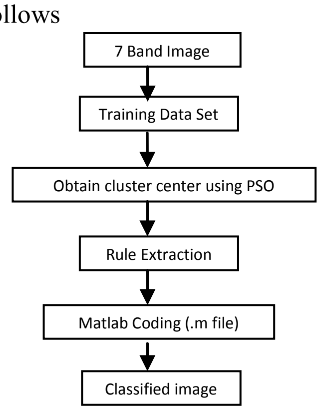

Figure A: Flowchart of Proposed Work

VI. CLASSIFICATION ERROR MATRIX

Error matrices compare, on a category by category basis, the relationship between the reference field data (ground truth) and the corresponding results of a classification. These are square matrices having equal number of rows, columns and categories (whose classification accuracy is being assessed). The major diagonal of the error matrix represents the properly classified land use categories. Kappa Coefficient is calculated for the image which turns out to be 70%.

The equation for the Kappa coefficient is given as

$$K = \frac{N \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+}X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i+}X_{+i}}$$

Where

r=number of rows and columns in error matrix

N =total number of observations

Xii=observation in row i and column i

Xi+=marginal total of row i and

X+i =marginal total of column i,

VII. CONFUSION MATRIX

A confusion matrix lists the values of known cover types of the reference data in the columns and the classified data in the rows. The main diagonal of the matrix lists the correctly classified pixels. One benefit of a confusion matrix is that it is easy to see if the system is confusing two classes(i.e. commonly mislabeling one as another). A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix.

VIII. OVERALL ACCURACY

One basic accuracy measure is the overall accuracy, which is calculated by dividing the correctly classified pixels(sum of the values in the main diagonal)by the total number of pixels checked. Besides the overall accuracy, classification accuracy of individual classes can be calculated in a similar manner. Two approaches are possible:

A. Producer’s Accuracy: Several other descriptive measures can be obtained from error matrix. The accuracy of individual category can be calculated by dividing the number of correctly classified pixels in each category by either the total number of pixels in corresponding row or column. Producer’s accuracies result from dividing the number of correctly classified pixels in each category (on the major diagonal) by the number of training set pixels used for that category(the column total).

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B. User's Accuracy: User's Accuracies is computed by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (the row total). This figure is a measure of commission error and indicates the probability that a pixel classified into a given category actually represents that category on the ground.

IX. TRAINING SET

A training set is a portion of a data set used to fit (train) a model for prediction or classification of values that are known in the training set, but unknown in other (future) data. The training set is used in conjunction with validation and/or test sets that are used to evaluate different models.

Training sets are used in supervised learning procedures in data mining (i.e. classification of records, or prediction of target values that are continuous.)

The expert has the attribute set *P* from the Indian Remote Sensing (IRS-P6) satellite optical band image set of 1...4 *i.e.* Red (R), green (G), near-infrared (N) and middle-infrared (M) bands. The ground resolution of these images from LISS-III, sensor is 23.5m.

The land use/land cover classification (y) with independent attributes set x consists of two sets of radar sat microwave images radarsat-1(r1) and radarsat-2(r2) and digital elevation model (d) data.

The training data set consisting of 1420 locations on the image is collected taking all the 7-band images together in order to avoid any ambiguity for confirmed training sites. The knowledge resident with the expert is assumed to be the one obtained from the training set, duly verified from ground checks and is confined to the r, g, n, m bands. This data set can be represented in a tabular form similar to that of a relational database tables. Rows of the table represent the training pixels and the digital values in the columns related to the 7-bands viz., r, g, n and m. The table has, therefore, 4 attributes (r,g,n and m), termed as attributes set p.

TABLE I: KNOWLEDGE RESIDENT WITH EXPERT

IMG 1	RED BAND	LISS-III/IRS-P6
IMG 2	GREEN BAND	LISS-III/IRS-P6
IMG 3	NEAR INFRARED	LISS-III/IRS-P6
IMG 4	MIDDLE INFRARED	LISS-III/IRS-P6
IMG 5	LOWINCI,S1,20^{O} - 27^{O}	RADARSET-1
IMG 6	HIGHINC,S7,45^{O}-49^{O}	RADARSET-2
IMG 7	DIGITAL ELEVATION MODE	(DEM) RES:25

X. RESULTS

From result, it is clear that PSO based Classification enhances the quality of an image .Accuracy % of the image is computed.

TABLE II: TRAINING SET

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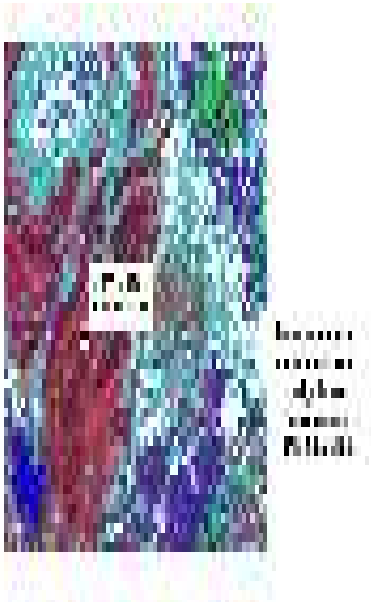

Figure: B. Image after Classification

Kappa Coefficient :0.70334

TABLE III: INTERPRETATION OF K VALUES

XIII . CONCLUSION

Figure:B shows the resulting classified image after applying PSO algorithm to the alwar dataset. In the figure dark blue color on the bottom left represents the water body, brown color represents the rocky area, green color represents vegetation, white color is barren area, sky blue represents the urban area. As it can be seen from the figure, the PSO algorithm is extraction of the minute details of the image.The value of the kappa coefficient for PSO is 0.7033 for the Alwar image.

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ACKNOWLEDGEMENT

I thanks, Mr. V.K.Panchal Scientist 'G', DRDO Delhi and all his team members for their support and guidance. I fail with my words, if I fail to thank my parents, my family, and god who made it possible.

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