Hybrid Algorithm of Cuckoo Search and Particle Swarm Optimization for Natural Terrain Feature Extraction

[1]Harish Kundra and [2]Harsh Sadawarti
[1]Punjab Technical University, Jalandhar, India
[2]Regional Institute of Management and Technology, Punjab, India

Corresponding Author: Harish Kundra, Punjab Technical University, Jalandhar, India

ABSTRACT

Swarm intelligence is a global research area to improve the optimization of various soft computing and nature inspired techniques. In this study, we have applied the hybrid algorithm of Cuckoo Search (CS) and Particle Swarm Optimization (PSO) for remote sensing image classification of natural terrain features. Remote sensing is the method of acquiring, processing and interpreting the satellite images and related geo-spatial data without any physical contact of that region. The main advantage of using the hybrid concept is that the search strategy used in CS for finding the best host nest for cuckoo egg is resolved by the best position of PSO concept. By using this proposed algorithm, it becomes easier to classify the terrain features and obtained results shows the higher efficiency and greater kappa coefficient value as compare to other swarm intelligence techniques. We have successfully applied the hybridization of Cuckoo Search (CS) and Particle Swarm Optimization (PSO) for classifying diversified land cover areas in a remote sensing satellite image.

Key words: Swarm intelligence, particle swarm optimization, cuckoo search, remote sensing, kappa coefficient, hybridization, terrain features

INTRODUCTION

Swarm intelligence is an innovative artificial intelligence technique that came under sight due to amazing efficiency and incredible abilities of social insects to solve their simple food/shelter related problems and is now accepted as one of the most efficient optimization technique (Bonabeau *et al.*, 1999). In 1989, swarm intelligence was first introduced by Beni and Wang (1989) in the global optimization framework as a set of algorithms for controlling robotic swarm (Beni and Wang, 1989). Due to highly efficient optimization behavior of swarm intelligence, it can be applied to a variety of applications including function optimization problems, finding optimal routes, scheduling, structural optimization, image and data analysis, machine learning, dynamical systems and operations research, image classification etc. Here, we are applying the hybridization of CS and PSO for remote sensing image classification of natural terrain. Remote sensing (Lillesand and Kiefer, 2000) is the technology to sense, observe and measure any object on the earth surface using data acquired from geo spatial satellite without any physical contact to that object and displays those measurements over a two dimensional spatial grid i.e., image. So, image classification plays an important role in the field of remote sensing for recognizing different terrain features. The intent of classification process is to categorize all the pixels of multispectral images into all the terrain features for almost all the regions like water, vegetation, urban, barren and rocky. Currently many soft computing and swarm intelligence techniques like fuzzy system, Membrane Computing (MC), Particle Swarm Optimization (PSO), Cuckoo Search (CS), Artificial Bee Colony

Optimization (ABC), Biogeography Based Optimization (BBO) and Genetic Algorithm (GA) are being used for image classification. Out of these two recent invented metaheuristic algorithms PSO and CS shows the high degree of efficiency for almost all the regions.

In this study we introduce a novel approach of hybridization of CS and PSO for remote sensing image classification to get higher efficiency and greater optimization value. Cuckoo Search (CS) is a new nature inspired metaheuristic algorithm, developed by Yang and Deb (2009) and is based on the brood parasitism of some cuckoo species. Particle Swarm Optimization (PSO) is a metaheuristic optimization technique introduced by Kennedy and Eberhart (1995) and is based on the intelligent, experience-sharing, social flocking behavior of birds. PSO is a population-based search algorithm that finds optimal solutions using a set of flying particles. Due to dominating features of these two algorithms, we are proposing a new algorithm by hybridization of CS and PSO and applying this metaheuristic proposed algorithm in the area of image classification. The main aim in this study is to classify the image into different terrain features and to compare the classification efficiency of this proposed algorithm with other soft computing and swarm intelligence techniques.

BASIC CONCEPTS

Cuckoo Search: Cuckoo Search (CS) is one of the latest nature inspired heuristic algorithm, developed by Yang and Deb (2009). It is based on the parasitism of some cuckoo species. This algorithm was further enhanced by the so-called Lévy flights, rather than by simple isotropic random walk methods.

Cuckoo is a fascinating bird, not only because of the mellifluous sound they can produce but also because of their aggressive reproduction strategy. In nature, an aggressive strategy of reproduction is used by cuckoos. It uses the female hack nest of other birds to lay their eggs inseminated (Payne *et al.*, 2005). Sometimes, the egg of cuckoo is discovered in the nest and the hacked bird discards or abandons the nest and starts their own brood elsewhere. The CS is based on the following three rules:

Rule 1: Cuckoo bird lays one egg at a time and dumps it in a similar nest that is randomly chosen

Rule 2: One of the best nests with high quality of eggs (solutions) will carry over to the further next generations

Rule 3: The number of possible host nests is fixed and the host can discover an alien egg with a probability factor $P_\alpha \in (0, 1)$. In this case, the host bird can either throw the egg away or abandon the nest so that it can build a completely new nest in a new location

The last assumption is approximated by a fraction P_α of the n nests being replaced by newly found nests (with new randomly found solutions at new locations). The generation of newly found solutions x_{t+1} is done by using the Lévy flight. Lévy flight essentially provides a random walk while their random steps are drawn from a Lévy distribution for large steps which has an infinite variance with an infinite mean. Here, the consecutive steps (jumps) of a cuckoo essentially form a random walk process which obeys the power-law step length distribution with a heavy tail:

$$X_i^{(t+1)} = X_i^{(t)} + \alpha \oplus \text{Lévy}(\lambda)$$

$$\text{Lévy} \sim u = t^{-\lambda}; \ (1 < \lambda \leq 3)$$

where, $\alpha > 0$ is the step size which should be related to the scales of the problem of interest. Generally, we take $\alpha = O(1)$. The product $\oplus$ stands for entry-wise multiplications. Here the

entry-wise product is similar to those used in PSO but the main difference is of efficiency. In CS the random walk via Lévy flight is more efficient in exploring the search space as compare to PSO because the step length in CS is much longer in the long run.

Particle Swarm Optimization (PSO): Particle Swarm Optimization (PSO) is a population-based search strategy that finds the best optimal solutions using a set of flying birds (particles) with velocities that are dynamically adjusted according to their historical performance, as well as their neighbors in the search space. It was introduced by Kennedy and Eberhart (1995) by capturing the behavior and intelligence of flocking birds (Kennedy and Eberhart, 1995). In PSO, each solution bird in flock is referred to a particle. The birds in the population evolve their social behavior only and accordingly their movement towards the destination.

As this bird flock fly, they starts communicating with each other to identify the bird at the best location. Similarly in the same manner, each bird speed towards the best located bird using a velocity that depends upon its current position. Then, each bird investigates the search space from its newly attained local position and the process repeats until the bird flock reaches at the desired destination.

This algorithm works in an iteration manner and moves closer to the best solution. The process is initialized with a group of random particles (solutions), N. The ith particle is represented by its position as a point in the S-dimensional space, where S stands for number of variables. Throughout this process, each particle i monitors three values: Its current position (X_i); the best position it reached in previous cycles (P_i); its flying velocity (V_i). These three values are represented as follows:
Current position of bird:

$$X_i = (x_{i1}, x_{i2}, \dots x_{is})$$

Best previous position of bird:

$$P_i = (p_{i1}, p_{i2}, \dots p_{is})$$

Flying velocity of bird:

$$V_i = (v_{i1}, v_{i2}, \dots v_{is})$$

In each time interval (cycle), the position (P_g) of the best particle (g) is calculated as the best fitness of all particles. Similarly, each particle updates its velocity V_i to catch up with the best particle (g), as follows:

$$V_i^{(t+1)} = \omega\, V_i^{(t)} + c_1 r_1 (P_i^{(t)} - X_i^{(t)}) + c_2 r_2 (P_g - X_i^{(t)})$$

In this way, the new velocity V_i of particle for the updated position becomes:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)}; \ V_{max} \geq V_i \geq -V_{max}$$

where, c_1 and c_2 are two positive constants named learning factors (usually $c_1 = c_2 = 2$); r_1 and r_2 are two random functions in the range [0, 1], V_{max} is an upper limit on the maximum change of particle velocity and u is an inertia weight employed as an improvement proposed by Shi and Eberhart (1998) to control the impact of the previous history of velocities on the current velocity.

The operator 'u' plays the role of balancing the global search process and the local search process and was proposed to decrease linearly with time from a value of 1.4-0.5. As such, global search starts with a large weight and then decreases with time to favor local search over global search.

METHODOLOGY

Hybridization of Cuckoo Search (CS) and Particle Swarm Optimization (PSO): Cuckoo search and particle swarm optimization are two stochastic search optimization algorithms that mimic the metaphor of natural biological evolution and social behavior of the species. The behavior of such species is guided by learning, adaptation and evolution. In these techniques fitness factor decides all of these characteristics.

In cuckoo search, cuckoo bird lay their reproductive egg in other bird's nest, though they may remove their eggs to improve the hatching probability of their own eggs. For this strategy, CS refers to the fact that the problem initially searches for current best solution and then aim for global solution. In particle swarm optimization, initially particles (birds) fly with a speed vector in solution space to find the best position for their food. Each particle has a memory to store its experience (i.e., its best position). Each particle maintains a distance from other particle and this process continues till each particle attains the best position so that the problem can be easily optimized. In our proposed algorithm we have replaced the behavior of cuckoo bird with the optimization technique of particles (i.e., birds) of PSO.

The main idea behind this hybridization of CS and PSO is that the search strategy for finding the nest for cuckoo bird in CS is replaced by the best position of the bird of PSO. In this way, when cuckoo bird try to search for best position of nest to lay its egg, then search process would be completed by search strategy of PSO. So, the cuckoo egg would be at best optimized position by using PSO technique. In this we can create a more optimized technique by integrating two best swarm optimization techniques. In this way, the proposed algorithm can give a more optimized and efficient solution for the complex problems. The framework of the proposed algorithm can be described as below:

Step 1: To classify the image into terrain features, training dataset and 7-band satellite image are considered as the input. Suppositions are made by assuming training dataset pixels as the host nest and feature classes as the cuckoo egg

Step 2: Initially, condider multispectral image and calculate the total number of pixels by finding the distance between cuckoo egg and the host nest

Step 3: After obtaining the distance, find the most similar host nest for cuckoo egg by using the search strategy of ant colony optimization

Step 4: Select the best host nest by calculating the Pearson correlation coefficient b/w the cuckoo egg and similar host nest

Step 5: The host nest having maximum correlation value is the best host nest for the cuckoo egg

Step 6: Find the class to which the best solution belongs based on the expert data

Classification based on proposed algorithm

Dataset considered: We have applied this hybrid concept for the classification of terrain image. For this, we have considered a multi-spectral, multi sensor and multi resolution image of Alwar area in Rajasthan with dimensions 472×546 for classifying the various terrain features. The satellite image of seven different bands listed as Red, Green, Near Infra-Red (NIR), Middle Infra-Red (MIR), Radarsat-1 (RS1), Radarsat-2 (RS2) and Digital Elevation Model (DEM). The Red, Green, NIR and MIR band images are taken from Linear Imaging Self Scanning Sensor-III (LISS), sensor
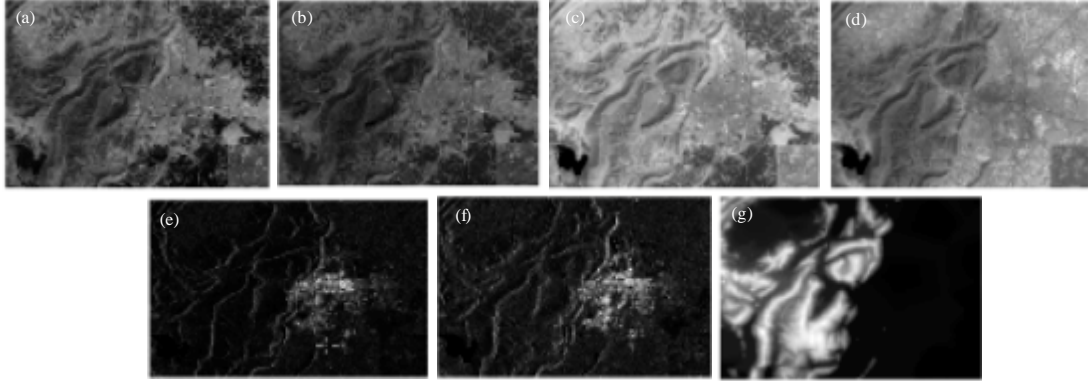
Fig. 1(a-g): The 7-band satellite image of Alwar Rrajasthan, (a) Red, (b) Green, (c) NIR, (d) MIR, (e) RSI, (f) RS2 and (g) DEM

of Resourcesat an Indian remote sensing satellite. RS1 and RS2 are the images from Canadian Satellite Radarsat. DEM is derived by using images from RS1 and RS2. The size of the image is 472×546 and it contains 2,57,712 pixels. The ground resolution of these images is 23.5 and 10 m, respectively from LISS-III and Radarsat-1. The green level 7-band satellite images of Alwar region are shown in Fig. 1.

Proposed algorithm
Assumptions:

- First outer loop = Total number of rows (egg)
- Second outer loop = Total number of columns (egg)
- Loop until all the pixels are being classified
- Inner most loop = Total number of dataset pixels (host nest)

Input: Training Dataset Pixels and Multispectral 7-band satellite image
Output: Classified image

Here, training dataset pixels are considered as the host nest and feature classes as the cuckoo egg.

Step 1: Consider the 7-band satellite image and calculate the total number of pixels by finding the distance between cuckoo egg and the host nest

Calculate the Euclidean distance between the each pixel of cuckoo egg and the host nest (7 band pixels) using the equation:

$$d(p,q) = d(q,p) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2} = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}$$

where, n = 1 to 7 band pixel values, d is the distance between the egg and host, p_i is the ith band pixel of cuckoo egg and q_i is the ith band pixel of host.

End of inner most loop

Step 2: Find the most similar host nests for cuckoo egg

The most similar host is found by the particle swarm optimization.

The similarity criteria is solved is the best similarity mean of the difference between the pixels intensities calculated.

Particle Swarm Optimization:

- Particle swarm optimization is initialized with a group of random particles (solution) and then searches for optima by updating the generations
- Each particle of PSO is flown through the search space, where its position adjusted based on its distance from its own personal best position and the distances from the best particle from the swarm
- The performance of each particle, i.e., how close the particle is from the global optimum is measured using fitness function which depends on the optimization problem
- Here our optimization problem is to find the mean of similarity difference of pixel intensities, given as:

$$f(x)= mean(sqrt((x-y)^2))$$

- Each particle flies through n-dimensional search space and maintains the following information
- X_i: Current position of particle (pixel intensities)
- P_i: The personal best position of particle
- V_i: The current velocity of particle
- The velocity updates are calculated as linear combination of position and velocity. Thus velocity of particle is updated as:

$$V_i^{(t+1)} = \omega V_i^{(t)} + c_1 r_1 (P_i^{(t)} \cdot X_i^{(t)}) + c_2 r_2 (P_g \cdot X_i^{(t)})$$

As such, using the new velocity V_i, the particle's updated position becomes:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)}$$

where, ω is inertia weight, c_1 c_2 are acceleration constant, r_1 r_2 are random numbers in range [0, 1]. V_i must be in predefined range $[V_{max}, V_{min}]$.

- The optimized mean is taken, the lesser the distance similar to the host pixel
- The host less than the mean are considered and the worst host nests are discarded
- The similarity host nests are stored

Step 3: Finding the best host nest

The best host nest is found by calculating Pearson correlation coefficient b/w cuckoo egg and a similar host nests calculated. The Person correlation coefficient is calculated as:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2} \sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

Step 4: The host nest having maximum correlation value is the best host nest for the cuckoo egg
Step 5: Find the class to which best solution belongs based on the expert data. The query pixel will also belong to the same class to which the best solution belongs. Hence the query pixel is classified

End second outer loop.
End first outer loop.
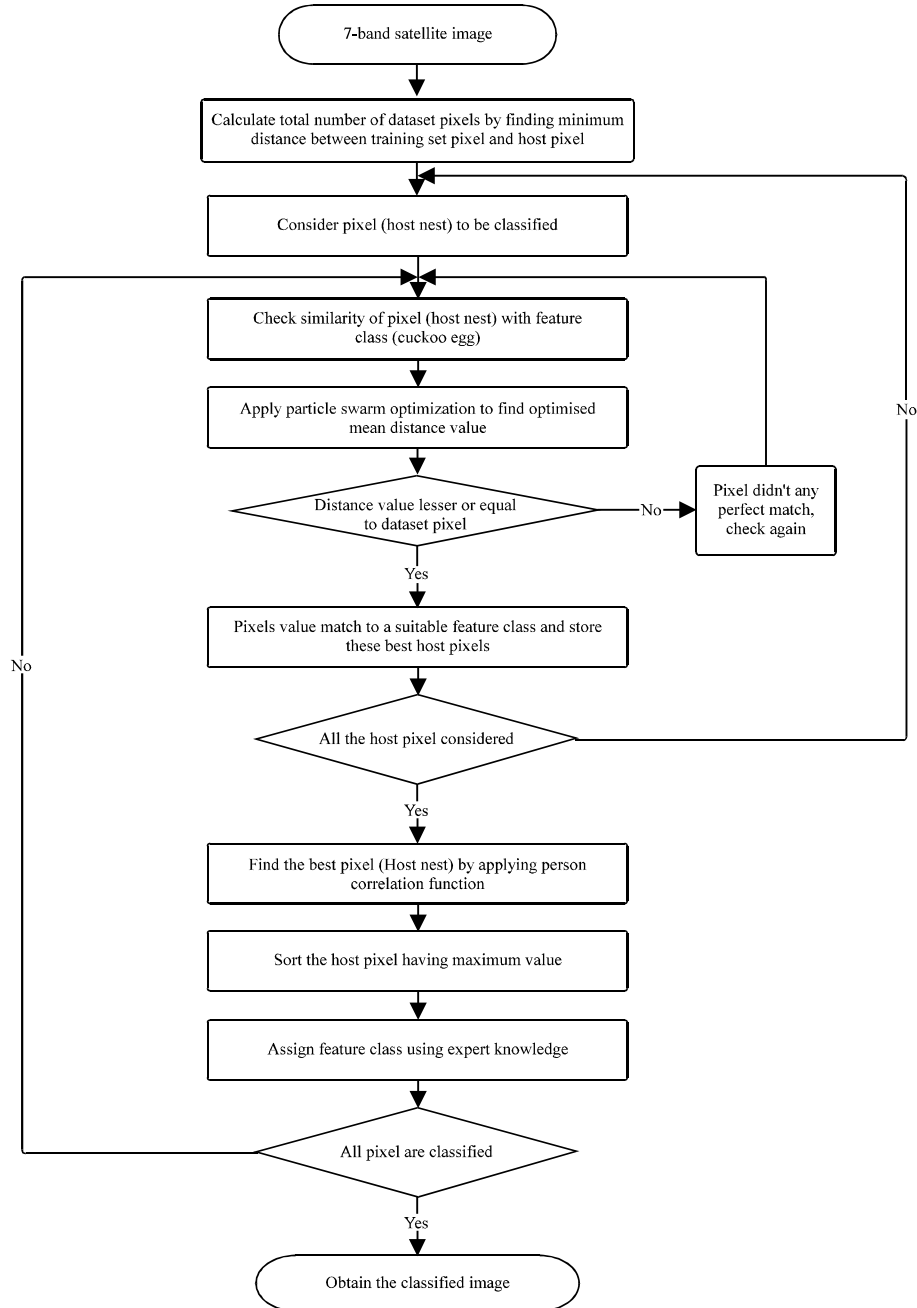The flowchart of proposed algorithm is shown in Fig. 2.

Fig. 2: Flowchart of proposed algorithm

RESULTS AND DISCUSSION

Image classification: We have used a multispectral, multi-sensor and multi-resolution image of Alwar region, Rajasthan in India. The size of the image is taken 472×546 pixels. The area is selected since it contains the good land cover features like water, vegetation, urban, rocky and barren areas. After applying the proposed algorithm to the Alwar image, the classified image is obtained with different classes. The different colors define the different terrain features in this image. The Red color represents water region, Green color represent vegetation region, Blue color represents urban region, Yellow color represents rocky region and Cyan color represents barren region. This classified image can be compared with the original satellite image as shown in Fig. 3.

Accuracy statement: To determine the efficiency of our proposed algorithm, we have to find the accuracy assessment in the image classification process. The goal is to quantitatively determine how efficiently the pixels were grouped into correct feature classes in the area under investigation. The classification accuracy is checked using the well-accepted error matrix in the field of remote sensing (Congalton, 1991; Story and Congalton, 1986; Verbyla and Hammond, 1995). Error matrices compare, on a category by category basis, the relationship between the known reference data and the corresponding results of an automated classification.

Practically it is not possible to test every pixel of a classified image. So, a set of randomly selected reference pixels is used for experimentation. Reference pixels are points on the classified image for which actual features are known. For validation process we have taken into consideration following number of pixels:

- Water pixels-74
- Vegetation pixels-161
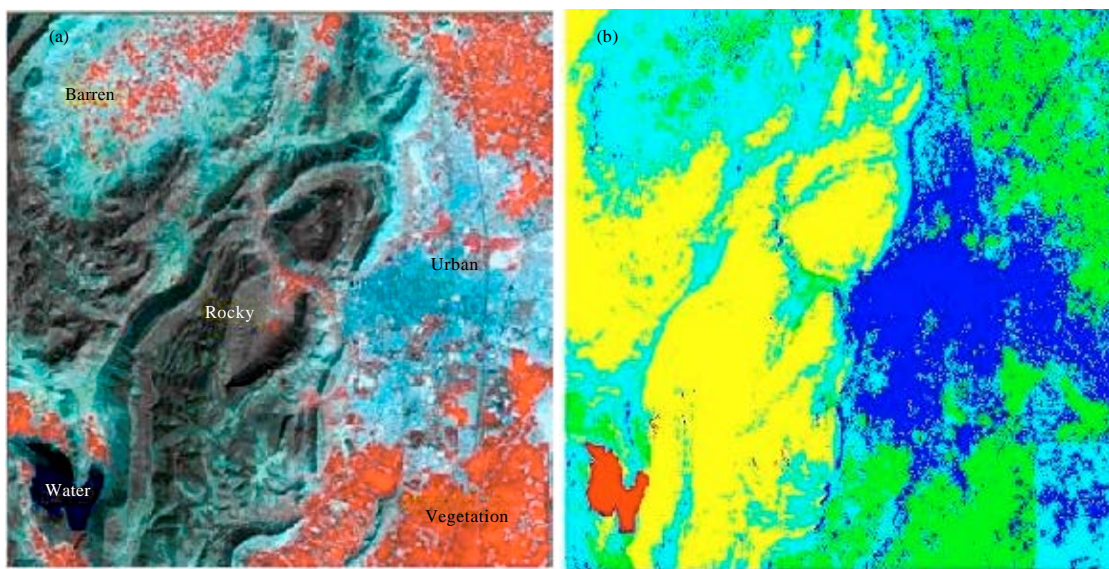- Urban pixels-149
- Rocky pixels-101
- Barren pixels-62

Fig. 3(a-b): Comparison of (a) Original Alwar image and (b) Classified image

Table 1: Error matrix after implementation of hybrid algorithm

Features	Water	Vegetation	Urban	Rocky	Barren	Total
Water	74	0	0	0	0	74
Vegetation	0	161	1	0	0	162
Urban	0	0	149	0	5	154
Rocky	0	0	0	101	0	101
Barren	0	0	10	0	62	72
Total	74	161	160	101	67	563

The various factors that can be considered for the accuracy assessment are explained with their calculated value in Table 1.

Kappa coefficient: The kappa coefficient is a discrete multivariate technique to interpret the results of error matrix. The kappa statistic incorporates the off diagonal observations of the rows and columns as well as the diagonal to give a more robust assessment of accuracy than overall accuracy measures. The kappa coefficient can be calculated by applying the following equation to the error matrix:

$$\tilde{K} = \frac{N \sum_{i=1}^{r} xii - \sum_{i=1}^{r} (X_{i+} \dots X_{+i})}{N^2 - \sum_{i=1}^{r} (X_{i+} \dots X_{+i})}$$

Where:
r = Number of rows in the error matrix (r = 5 in our case)
x_{ii} = The number of observations in row i and column i (on the major diagonal)
x_{i+} = Total of observations in row i (shown as marginal total to right of the matrix)
x_{+i} = Total of observations in column i (shown as marginal total at bottom of the matrix)
N = Total number of observations included in matrix (N = 563 in our case)

The kappa coefficient of the Alwar image for the proposed algorithm is 0.9633 which indicates that an observed classification is 96.33% is better than the one resulting from chance.

Producer's accuracy: Producer's accuracy is a measure of how much of the land in each category was classified correctly, i.e., how accurately the analyst classified the image data by category (columns). This is calculated as:

$$P = \frac{\text{No. of correctly classified pixels in each category (on major diagonal)}}{\text{Total number of training set pixels used for that category (the column total)}}$$

After applying proposed algorithm, the producer's accuracy is calculated shown in Table 2.

User's accuracy: User's accuracy is a measure of how well the classification performed in the field by category (rows). This is calculated as:

$$U = \frac{\text{No. of correctly classified pixels in each category (on major diagonal)}}{\text{Total number of pixels used classified in that category (the row total)}}$$

After applying proposed algorithm, the user's accuracy is calculated as shown in Table 2.

Overall accuracy: Overall accuracy is the number of correct observations divided by the total number of classifications. This is a very crude measure of accuracy and can be calculated as:

$$O = \frac{\text{Total nomber of correct classifications (Sum of all values on major diagonal)}}{\text{Total number of classifications}}$$

The overall accuracy of proposed algorithm for Alwar image is 97.15% which indicates that the observed value is far better than others.

Comparison with CS and PSO: To compare the accuracy of proposed algorithm with other CS and PSO, we will consider two parameters as listed below:

Kappa coefficient: The value of kappa coefficient for proposed algorithm is 0.9633 which shows that the observed classification is better as the kappa coefficient of some other algorithms are fuzzy set (Banerjee *et al.*, 2012), BBO (Panchal *et al.*, 2009b; Goel *et al.*, 2011a), PSO (Panchal *et al.*, 2009a), ABC (Banerjee *et al.*, 2012), CS (Bharadwaj *et al.*, 2012), hybrid rough/BBO (Goel *et al.*, 2011b), hybrid fuzzy/BBO (Goel *et al.*, 2011a) are 0.9137, 0.68812, 0.7033, 0.917, 0.9465, 0.6715, 0.6912, respectively. The graphical comparison of these algorithms is shown by Fig. 4.

Overall accuracy: The overall accuracy of terrain classification for proposed algorithm is 97.15% which shows that the observed classification is better as the value of overall accuracy of BBO, PSO, ABC, CS, fuzzy set, hybrid rough/BBO, hybrid fuzzy/BBO are 75.80, 80.34, 93.47, 95.78, 93.13, 74.23 and 75.76%, respectively. The graphical comparison of these algorithms is shown by Fig. 5.

Table 2: Producer's and user's accuracy of each feature

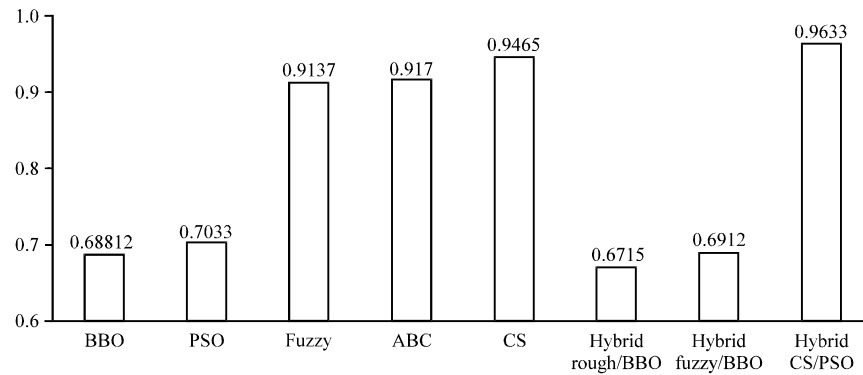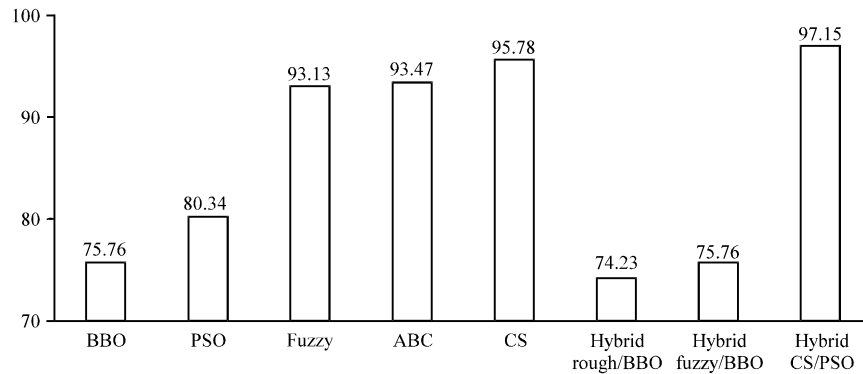| Accuracy	Features (%)				
	Water	Vegetation	Urban	Rocky	Barren
Producer's accuracy	100	100	93.12	100	92.53
User's accuracy	100	99.38	96.75	100	86.11

Fig. 4: Comparison of kappa coefficient

Fig. 5: Comparison of overall accuracy

CONCLUSION

In this study, we have proposed the hybrid technique of cuckoo search and particle swarm intelligence for the image classification of terrain features. Even all of the discussed algorithms give high accuracy value for image classification individually but when proposed hybrid algorithm was applied then the accuracy for image classification became amazing as compare to the individual algorithms. From the comparison (Fig. 4, 5) we have also successfully shown the high performance of proposed algorithm concept of replacing the search strategy of CS to find the best host nest with the best position of PSO algorithm. Thus our proposed algorithm for the classification of image was successfully able to extract the terrain features from the given dataset and also maintains high level of classification accuracy.

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