Classification of remote sensed data using hybrid method based on ant colony optimization with electromagnetic metaheuristic

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In this study, a hybrid configuration of electromagnetic metaheuristic algorithm (EM) with *Pachycondyla apicalis* (API) ant algorithm (inspired by the behaviour of real ant colony *Pachycondyla apicalis*) belonging to ant colony optimization (ACO) called EMAPI algorithm is presented for remote sensing data classification. The traditional per-pixel classification method identifies the classes using spectral variance and ignores the spatial distribution of pixels. It requires training data to be normally distributed in the pixels corresponding to land use/land cover classes and creates a lot of confusion between classes within a remote sensed (RS) data. The proposed algorithm is an integrated strategy structure to achieve advantages of global and local search ability of EM and API algorithms respectively. The objective consists of improving overall accuracy of the classified results of RS data. This method can overcome intermixing with regard to scrub land with cultivated areas and build-up land with palm groves. The proposed algorithm is tested on objective functions well used in the literature and EMAPI is used for supervised land cover classification. Results of EMAPI algorithm over 6 classes showed an improvement of 8% in overall classification accuracy (OCA) for EM technique and improvement of 3% in OCA for API algorithm.

Keywords: Ant colony optimization, API algorithm, electromagnetic metaheuristic, data classification, hybrid metaheuristic.

IN recent years, remote sensing data classification has become attractive due to its technical, economic and environmental benefits. Basically this processing is difficult because regions of land cover features lead to confusion of two or more regions. Precisely, pixel values are assigned based on their reflectance of classes present in that area. Supervised, unsupervised and semi-supervised are the three popular learning techniques for land cover classification[1–3]. Numerous computational artificial intelligence techniques have been used, e.g. fuzzy logic[4], neural network[5], support vector machine[6] and K-means[7]. Metaheuristics have also been widely used for remote sensing data classification[8,9], e.g. particle swarm[10], ant colony techniques[11–13], bee colony[14], artificial immune system[15] and genetic algorithm[16].

Generating a satisfactory classified image from the higher spectral, spatial and temporal resolution, and high-dimensional (bands) data is one of the present-day challenges in RS data[17,18]. Hence, this study is aimed at developing a new classification technique to improve classification accuracy even when a subjective and objective numerical approach is adopted.

Several studies are based on stochastic and collective behaviour with a decentralized approach which significantly improves the searching capability of optimization algorithm. Hybridizing local search technique with global optimization metaheuristics provides a reliable classification approach for data with a mixture of vegetation, urban and semi-urban land cover and a large number of spectrally overlapping subclasses[19–21]. The purpose of global optimization technique is to maintain a scatter population to explore the whole area of interest. However, improving the accuracy of a solution by exploring its neighbourhood is dedicated to the local search algorithm[22]. The ultimate goal of hybrid method is to best exploit spectral, spatial signature of the data to avoid other inherent characteristic associated with it[23]. The present study develops a hybrid EM-ACO technique named EMAPI to classify remotely sensed data.

The present work aims to avoid the drawbacks of API algorithm[15,24] and study performance of EM which is dependent on local search[25]. This way, EMAPI algorithm takes advantages of the local search for EM technique and the downhill (gradient descending) search behaviour of API algorithm.

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Methodology

Metaheuristics algorithms offer high quality solutions through global optimal solution by reducing CPU time[15].

Today, utilization of metaheuristics algorithms has drawn great attention in several data processing fields due to reduction in computational time and global optimal solutions[19]. The present study focuses on the concept of hybridization, which is a good idea for optimization to increase the results of classification.

In this article, two metaheuristics are used: the first is an API algorithm and the second is an EM technique inspired by attraction–repulsion mechanism of charged particles.

API algorithm

The API *Pachycondyla apicalis* (API) ant algorithm[26] differs in terms of search strategy from the basic of ACO, where API memorizes and navigates the routes instead of using only chemical substances called pheromones.

API algorithm was inspired by the behaviour of real ant colony called *Pachycondyla apicalis*, which lives in the Mexican tropical forest near the Guatemalan border. The biological aspect of this colony was studied by Fresneau[27,28]. The classes were discovered and classified using an approach similar to the collective process of seeking food by ants. API algorithm obtains a set of rules in the training set through a sequential process which iteratively finds the best classes which cover most pixels in the training sample.

Given below are different steps of the API algorithm.

Step 1: Nest sampled randomly in the search space

- Depending on the brightness value of each class the remote sensed data has been noted with different classes.
  Ants sampled randomly around the nest
  For each ant
  Creating haunting sites
- Starting from class 1 to class n, API ant adds nodes to the classes to classify the data according to the chemical substance obtained at each node.
- New classes are identified in its neighbourhood and exploit the other classes in its predefined training site.
  Exploring haunting sites
- if the class identified was unsuccessful, then it exploits the previously assigned class again.
- Erase sites: when the data are misclassified consecutive number of times, unsuccessful contents are erased from the memory of ants.

Step 2: If (f (best ant) < f (nest)) then the nest moves to best ant's location.

- If all the pixels are correctly classified, dataset has been erased from memory and waits for the new dataset.
  Until condition criterion is reached.

Return (nest position)

- If all the classes are classified correctly remove the training sample which has been finally covered by the ant.

EM algorithm

Electromagnetic metaheuristic is a global optimization algorithm inspired by attraction and repulsion of electrical charges. This algorithm was proposed by Birbil and Fang[25] for complex optimization problems with bounded variables.

This metaheuristic has been used for several problems. For example: solving the maximum betweenness[29], the unicost set covering problem[30] and the nurse scheduling problem[31]. The general scheme of EM algorithm is shown in Figure 1.

The first procedure in the algorithm named Initialize() is used to sample m particles from the search space. As a result, initializing in EM algorithm using k-means algorithm helps choose training samples by addressing different initial centres to find the best solution. If there is a mismatch with training and testing data, the classification will lead to incorrect results.

The purpose of the second procedure (named LocalSearch( )) is to allocate the local search information to each particle in the population. Initial centres for each class are gathered from the density function of various points from the first principal component (PC) which are set to ((–0.68, –0.37); (0.09, 2.08); (0.26, 0.92); (2.23, –0.32); (3.18, –0.66); (3.48, –0.55)).

In this study, we used a simple local search as used in earlier[25]. The third procedure named CalcForce() is dedicated to calculate the total force (F^i) exerted on each

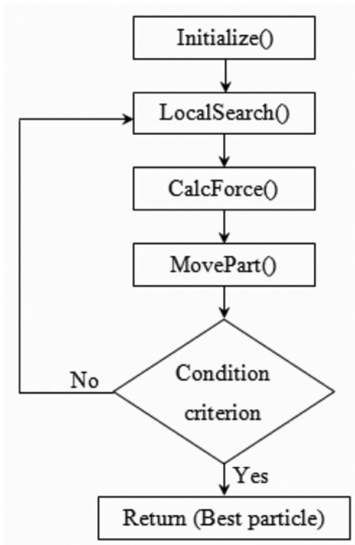

Figure 1. EM flowchart.

particle i (eq. (2)). To enhance and compress the pixel values, a low and high resolution image is processed using logarithmic transformation to satisfy the maximum likelihood classifier which supports Gaussian distribution process. As a result, it is used to classify the classes correctly.

The charge of each particle (q^i) is required to calculate F^i (eq. (2)). The charge q^i (eq. (1)) of particle i can be calculated as follows

$$q^i = \exp\left(-n\, f(x^i) - f(x^{\text{best}}) \Big/ \sum_{k=1}^{m} (f(x^k) - f(x^{\text{best}}))\right); \forall i, \quad (1)$$

$$F^i = \sum_{j \neq i}^{m} \begin{Bmatrix} (x^j - x^i) q^i q^j / \| x^j - x^i \|^2 \text{ if } f(x^j) < f(x^i) \\ (x^i - x^j) q^i q^j / \| x^j - x^i \|^2 \text{ if } f(x^j) \geq f(x^i) \end{Bmatrix}; \forall i, \quad (2)$$

The last procedure MovePart() permits to move the particle i in the direction of the force exerted on it (eq. (3))

$$x^i = x^i + \lambda F^i / \| F^i \|. \quad (3)$$

Figure 2 presents the base principle of EM algorithm. For more details about EM algorithm readers could refer to Birbil and Fang[25].

EMAPI algorithm

The proposed EMAPI metaheuristic is mainly the API algorithm used in local search step of EM technique to solve global continuous optimization problems of moderate and large dimensional datasets. Hybridization, entitled EMAPI, keeps the 'downhill' search ability of API, to avoid trapping of local minimum sectors by using the concept of diversity given by the EM metaheuristic. The proposed algorithm can reduce time and can provide an appropriate solution compared to other algorithms, due to distributed work load among them which is spectrally homogeneous and spectrally overlapping. The best solutions are identified by API algorithm when added with EM local search pool which follows the iterative process proportional to their fitness and distributes the workload among all workers and provides optimal solution to the classified results. During the search, the best fit in API is identified through fitness proportional scheme and through pheromones evaporation.

First, the proposed algorithm selects an individual particle for initializing the population to encode the food source for classification. In EMAPI, algorithm variables are represented using string values, where each particle is optimized using fitness values of API algorithm. Secondly, API algorithm is used as local search step. Later the charges of each particle (eq. (1)) are computed to obtain the total force (eq. (2)) exerted on each one. After evaluating the total force, each particle is moved to a new position on the search space (eq. (3)). These precedent steps are repeated until a predefined number of iterations is reached. The structure of the proposed hybrid EM-API algorithm is shown in Figure 3.

For EM algorithm, parameters are initialized using k-means algorithm, where the number of iterations and time can be reduced for the obtained estimated parameters compared to API algorithm for each set of iterations which can provide increased log-likelihood until a local maximum is reached.

Local search step using API algorithm

Generation of new nest (exploration): It identifies new classes to avoid mixed pixels in the data.

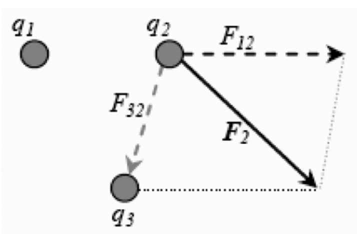

Figure 2. Principle of particles moving.

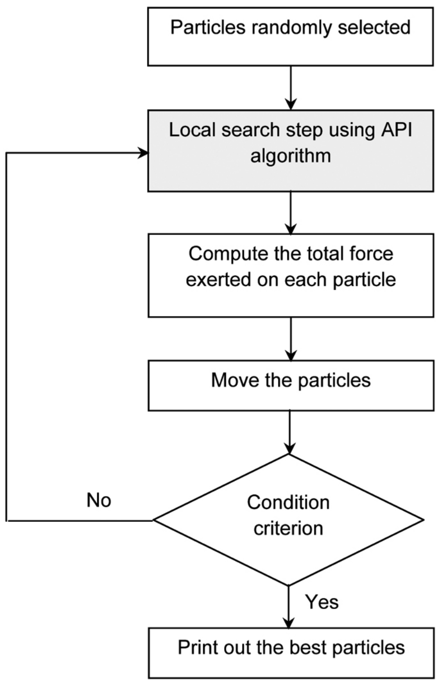

Figure 3. EMAPI flowchart.

Exploitation

Intensification search is based on the density function of the first principal components (FPC). For each ant, classes are assigned based on the behaviour of FPC. If the identified classes in its memory are less than a training sample, then it identifies new classes in its neighbourhood and exploits the other classes in its predefined training site; else if the class identified was unsuccessful; then explore the misclassified class; else explore the selected class which probabilistically matches in ant memory; end; end.

Erase sites: If the predefined classes are misclassified within 3 to 4 iterations, ant erases all the classes from its memory content.

Information sharing

To calculate the force, two ants share/exchange their class information depending on fitness values that are stored in the memory of the ant which can enhance or compress the pixel values to lower and higher intensity value. The EM technique shares information and distributes classes using the parameters of maximum likelihood estimator to avoid incomplete observations through Calcforce( ).

Move the particles

If the condition for nest movements is satisfied, go to classified result; else, go to the step intensification; end.

Best particle

All the pixels are classified correctly, STOP.

A lot of condition criteria could be used to stop an optimization algorithm, for example: (a) iterations are predefined, (b) successive number of iterations spent without improving the best particle, (c) a predefined maximum number of function evaluations. In this article, the first and the third criteria are used.

Training sample selection

To yield acceptable classification results, the training data or training sample (TS) must be both representative and complete in respect of the LU/LC of interest. The TS, in classification, allows analysts to tie known characteristics of LU/LC on the ground with reflectance values from a satellite image. The sample size is also a major issue in TS, since it is a function of image resolution and spectral characteristics of the classification of interest. For example, in this study a multi-spectral image of LISS-IV of 5.8 m spatial resolution over approximately 300 acres of land would contain 418,984 (image size: 664 × 631) pixels over the same land-area and scene. Even for such a small study area, a sample of just 0.5% of the total pixels would comprise training pixels or instances as huge as 2,094 and 4,925 per image band respectively, for the two images mentioned in the example. Practically, access to various portions of the study area is also quite difficult due to the complexity of terrain, security restrictions, cost and other constraints involved therein. Therefore, the size of the training data set needs to be kept small but must be large enough to accurately characterize and represent the LU/LC classes. Hence, the sample size is a major issue of debate in remote sensing, and has led to the following two arguments as observed in the literature. In this study a theoretical lower limit of $(n + 1)$ pixels is kept for considering in a training set, where n is the number of spectral bands. However, minimum 10 n to 100 n pixels should be selected for the necessary estimation to show an improvement in the training set. But due to statistical validity and practicality, if the size of pixels or the number of classes is more than 6, then at least 75 to 100 samples should be taken per class. Although the rule of thumb of having 75 to 100 samples per class is just an empirical approach, it should be favoured in practice to make sure that the statistical analysis and calculation of kappa are valid in RS data classification.

Figure 4 depicts the convergence of accuracy with training samples and validation sites. When the number of training samples per class is minimum, it is obvious that it is less convergent. The convergence is better as the training samples per class increase. The relationship changes when minimum training sample per class is 20 by achieving an overall classification accuracy of 80%. A total of 5 min was taken to classify the data using EMAPI algorithm.

Data used, study area and accuracy assessment

IRS-P6 LISS-IV satellite data captured on 26 December 2014 (path: 104, row: 028; 5.8 m spatial resolution)

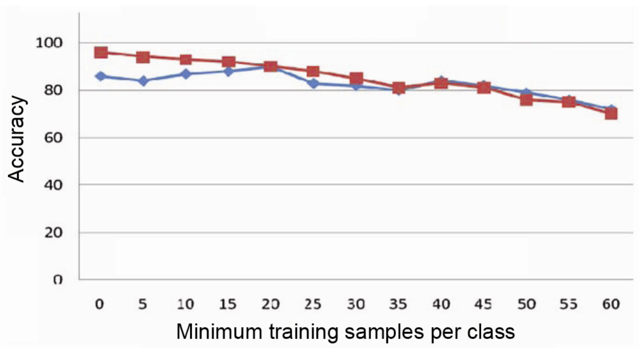

Figure 4. Behaviour of test sample and training sample error as a model complexity is varied. Red colour shows a training set and blue colour shows a testing data set.

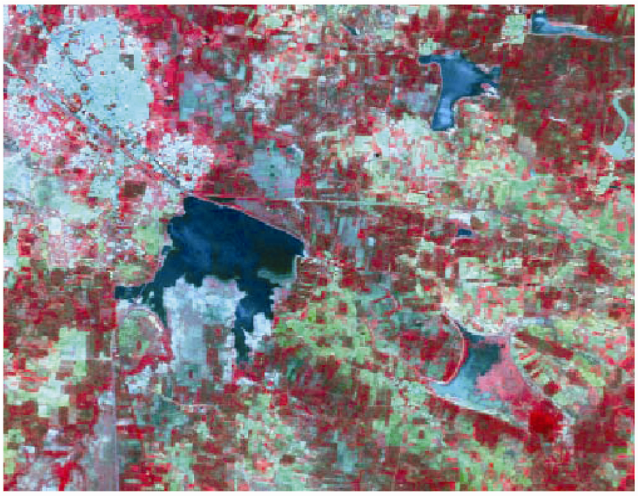

Figure 5. Arsikere study area.

consisting of three multispectral (MS) bands recorded at green (0.52 to 0.59 μm), red (0.62 to 0.68 μm) and infrared (0.77 to 0.86 μm) wavelengths, were used in this study. The area chosen for our work is semi-urban region of Arsikere with geographical co-ordinates between 1316′01.99″N to 1319′38.54″N and 7614′36.14″E to 7618′38.67″E with elevation of 0.0 m AMSL as shown in Figure 5.

Accuracy assessment

The two most commonly adopted accuracy assessment measures are the overall classification accuracy (OCA) and the kappa statistics computed from the error matrix. To avoid the bias from class to class accuracy in test data, it is important to consider the individual class accuracies under the producer's and user's accuracies where column represents reference data and row indicates classification generated from the RS data.

Overall classification accuracy: It is obtained by dividing the summed up values of row and column diagonally of the error matrix by the total number of classified pixels of the reference points in the error matrix.

$$\mathrm{OCA} = \sum_{i=1}^{k} n_{ii} / n. \tag{4}$$

Producer's accuracy: Producer's accuracy (PA) is obtained by dividing the total number of correctly classified pixels in a category (on the major diagonal) by the total number of pixels of that category as derived from the reference data (the column total). PA can be computed by

$$\mathrm{PA} = n_{ij} \Big/ \sum_{k=1}^{k} n_{ij}. \tag{5}$$

Error of omission = 100% – PA.

User's accuracy: User's accuracy (UA) can be obtained by dividing the total number of correctly classified pixels in a category (on the major diagonal) by the total number of pixels that are classified in that category (the row total). The user's accuracy can be computed by

$$\mathrm{UA} = n_{ii} \Big/ \sum_{i=1}^{k} n_{ij}. \tag{6}$$

Kappa statistic: The Kappa statistic is a measure of the difference between actual agreement between reference data and an automated classifier, and the chance agreement between the reference data and a random classifier

$$\mathrm{Kappa} = n\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{i+}n_{+i} \Big/ n^2 - \sum_{i=1}^{k} n_{i+}n_{+i}. \tag{7}$$

Results and discussion

The objective of the behavioural study is to investigate the response of EM, API and hybrid EMAPI algorithm on remotely sensed data and selection of classes which are dominated over a semi-urban area. API, EM and hybrid EMAPI classifications were accomplished using MATLAB software and validations were accomplished in Environmental Vegetation Index (ENVI) image processing software.

Figure 6 *a–c* shows visual comparison of hybrid algorithm, API and EM procedure for the 2014 year data. EM shows a misclassification in urban area and wasteland, whereas API algorithm distinguishes both the classes better. The classification results for API, EMAPI and EM are given in Tables 1–3 respectively.

An OCA of 83.97% was obtained in EMAPI, and 80.56% in API algorithm, where as in EM procedure OCA was found to be 72.97% for same number of training pixels.

- For class 1(built-up land) the performance of EMAPI algorithm is far better in comparison with EM (PA: 7.22% and UA: 12.72%) and API shows results closer to the proposed method.
- For class 2 (cultivated area) EMAPI algorithm shows an improvement of 6.22% in PA and 8.45% in UA when compared to EM algorithm but for API algorithm there is an improvement in PA of 2.51% and UA of 0.62%.
- For class 3 (water bodies) EMAPI algorithm shows an improvement of 7.14% in PA for EM algorithm, but there was a marginal improvement of 3.57% in PA and 25.72% in UA over API procedure.

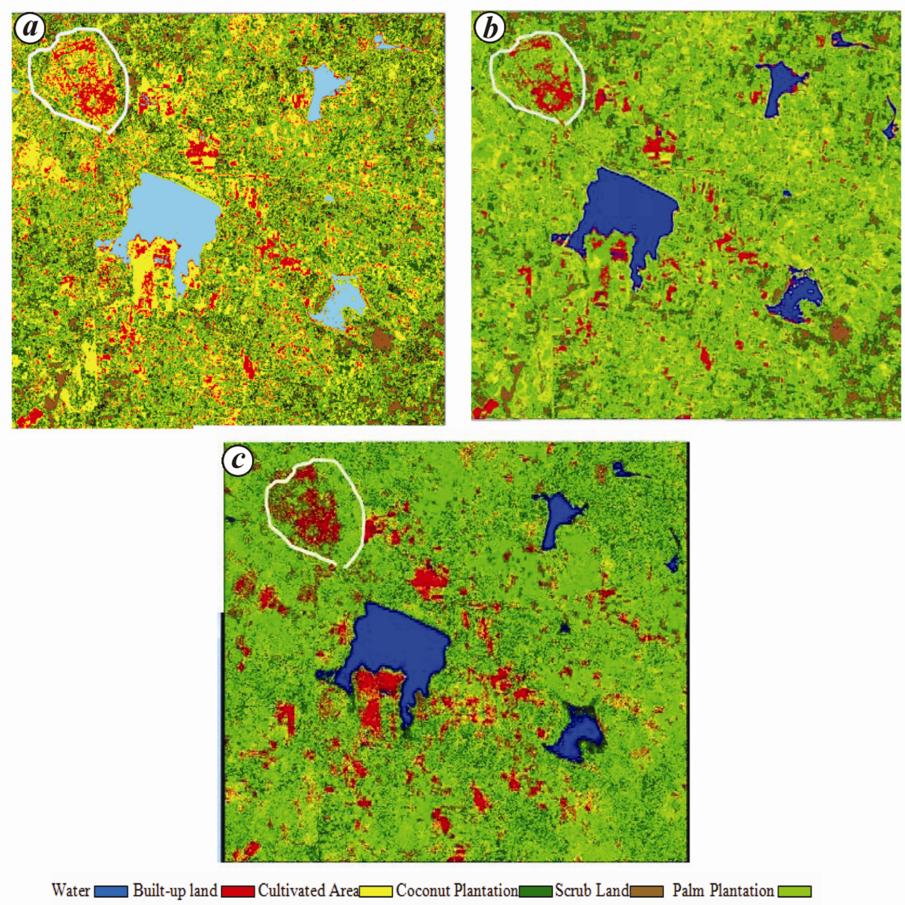

Figure 6. Classified multi-spectral image using (***a***) EM algorithm, (***b***) API algorithm, (***c***) EMAPI algorithm.

Table 1. Confusion matrix and conditional kappa values for the 6 classes using API

Classes	1	2	3	4	5	6	Row total	UA (%)
1	141	1		2	8	1	153	92.15
2	2	152			4		158	96.20
3	1		26	1	6	1	35	74.28
4		2		170	20		192	88.54
5		3	2	5	198		208	95.19
6		1		11	3	30	45	66.66
Column total	144	159	28	189	239	32	791	
PA (%)	95.83	93.08	92.85	84.65	82.84	84.37		OCA 80.56
kappa	0.904	0.93	0.746	0.816	0.791	0.821		

1, Built-up land, 2, Cultivated area, 3, Water bodies, 4, Coconut plantation, 5, Shrub land, 6, Palm plantation.

Table 2. Confusion matrix and conditional kappa values for the 6 classes using EMAPI

Classes	1	2	3	4	5	6	Row total	UA (%)
1	140			2	10	2	153	91.50
2	2	148		3	1		154	96.10
3			27				27	100
4	2	4		170	11		187	90.90
5		2	1	12	214	3	239	89.53
6		5		2	1	27	35	77.14
Column total	144	159	28	189	239	32	791	
PA (%)	97.22	95.59	96.42	92.89	89.53	94.75		OCA 83.97
Kappa	0.891	0.904	0.861	0.820	0.797	0.796		

Table 3. Confusion matrix and conditional kappa values for the 6 classes using EM

Classes	1	2	3	4	5	6	Row total	UA (%)
1	130		1	23	10	1	165	78.78
2		142	1	16	3		162	87.65
3			25				25	100
4	4	5		130	92	3	234	55.55
5	10	9	1	18	131	1	170	77.05
6		3		2	3s	27	35	75.14
Column total	144	159	28	189	239	32	791	
PA (%)	90.27	89.30	89.28	68.78	54.81	83.31		OCA 72.97
Kappa	0.899	0.934	0.96	0.542	0.532	0.724		

- For class 4 (coconut plantation), EMAPI algorithm exhibits an improvement of 24.11% in PA and 35.35% in UA over EM procedure whereas there is an improvement of 8.24% in PA and 2.36% in UA over API procedure.
- For class 5 (shurb land), the EMAPI algorithm shows an improvement of 34.72% in PA and 12.48% in UA over EM, whereas API algorithm produced a marginal improvement of 6.69% in PA and 5.60% in UA.
- For class 6 (palm plantation), EMAPI algorithm shows an improvement in PA of 11.44% and UA 2% when compared to EM algorithm and EMAPI performs better than API with a difference of 10.38% PA and 10.48% UA for class 6.

Conclusion

This study has proposed EMAPI hybrid algorithm for remote sensing image classification of semi-urban area near Arsikere district, which often displays a fragmented, heterogeneous land cover features on LISS-IV data of 5.8 m spatial resolution for 6 land cover classes which arise from absent or ineffective local planning. Electromagnetic metaheuristic algorithm is implemented in local search stage to improve the performance of API algorithm. The results obtained on test functions show that EM technique helps API algorithm to not only efficiently perform local exploration, but also effectively reach optimal or near optimal solution. The comparison results (results of the first problem) with other optimization techniques (EM, API, EMAPI) show that there is a scope of research in hybridization to solve complex optimization problems. The improvement of 83.97% in OCA was shown in EMAPI algorithm when compared with API (80.56%) and EM (72.97%) for the 2014 year data.

Compared to API and EM algorithm, EMAPI shows better classification results for the semi-urban region of the study area with improvement in water bodies, coconut plantation, shrub land and palm plantation.

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