

A Hybrid ACO based Optimized RVM Algorithm for Land Cover Satellite Image Classification

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Abstract

The proposed different classification schemes based on modified RVM and Optimized RVM were implemented, and observed the classification outputs. The proposed Optimized RVM classification technique is successfully applied to the classification of the input images. The quantitative and qualitative classification results are evaluated and compared. The accuracy of the proposed modified RVM is improved by applying the Ant Colony Optimization (ACO) technique. The kernel parameter of the modified RVM is optimized using ACO, and the results got improved a little better than the modified RVM based classifier. The general agreement between all classification techniques discussed in the above sections indicates that the inclusion of ACO for RVM parameter optimization adds very accurate classification in various multispectral satellite images. The performance evaluations confirm that the proposed ACO based Optimized RVM (ACO-RVM) classifier greatly improved the accuracy of final classification outputs.

Keywords: satellite Image classification, Ant Colony Optimization, Optimized RVM

Received on 24 October 2020, accepted on 08 December 2020, published on 23 December 2020

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doi: 10.4108/eai.23-12-2020.167789

1. Introduction

The proposed modified probabilistic-based RVM classifier algorithm has been implemented, and the classification results were observed in the previous module of this research. The modified RVM was implemented initially as an extension of the SVM classifier and produced satisfying results. The performance can be enhanced by optimizing the RVM kernel width parameter. The Ant Colony Optimization (ACO) technique is best suited to optimize the kernel width parameter of RVM and is called the Optimized RVM.

The proposed technique improves the automatic classification of multispectral imagery containing various land classes. The information on the study area and the dataset is provided following the information about multispectral satellite imagery. This chapter focuses

mainly on the proposed technique's fundamental steps, essential for the land cover clusters' automatic classification from the pre-processed image. The proposed classification scheme integrates data pre-processing, feature extraction, and classification.

The proposed technique can then be compared with the existing technique to validate the results obtained. The proposed system comprises the following modules like Image Acquisition, pre-processing, Feature Extraction, and classification. The image acquired is pre-processed by a Gaussian filter to remove the speckle noise present. Feature extraction is an important step in the land cover classification because it extracts different classes' discriminating features. Texture features are extracted from the de-noised input image.

In the proposed method, the Wavelet Transform Co-occurrence Features (WTCFs) are extracted from the first level wavelet decomposed input patterns, and these features are used for classification. The ACO based

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approach is used in the proposed system to attain the optimum kernel parameter of the classifier. This work analyses the performance of the proposed novel classification scheme for the classification of satellite images. A 7x7 window-sized matrix is subjected to wavelet decomposition from the pre-processed image's cropped regions where WTCFs were extracted and used in the training and testing phase using the optimal window selection method. Thus the classifier's decision finally segregates the different land classes such as building, vegetation, water, barren land, etc.

2. Literature Survey

Sukhendu Das et al. [1] uses Probabilistic Support Vector Machines to classify only roads from remote sensing images without concentrating on contrast and linearity. The method adopts four individual systems, making the system complex concerned with urban/ rural land mapping. The information is coordinated, utilizing an enhancement structure to acquire proper extraction on roads. It gives not too bad outcomes in circumstances just when the streets have extracted along with some obstacles such as trees, substantial vehicles, and tall structures. Connecting of disjoint sections utilizes the neighborhood slope functions at the nearby combining of road endings. It is found discrepancies to differentiate non--road structures to enhance the exactness in road location. Results are assessed with a vast dataset of high-resolution multispectral images but lead to road extraction along with commission errors.

Dengxin Dai and Wen Yang [2] proposed a high-resolution image classification strategy, including visual consideration in land class interpretation. It makes the technique focused on different structures 2) taking care of the satellite image classification without the learning stage. The experiments were conducted on various real satellite images. A two-layer sparse coding (TSC) model is intended to find the "genuine" neighbors and avoid the satellite image classification's painful learning period. The reconstruction of images using sparse representation technique is used where new image patches are the frame dependent on the sparse coding. This algorithm is implemented without considering the training stage. It leads to certain limitations of misclassification on similar texture pattern.

Guofeng Sheng et al. [3] proposed a Sparse Representation based model that has gained glorious achievement for remote sensing applications. The authors presented a structure-based sparse coding technique by combining light codes and structural grouping. They also compared their method with conventional sparse representation with codebooks. They said that their approach provides a fruitful classification in land cover mapping tasks. The reference database of 21 land use classes was utilized from which features were extracted. The demonstration test outcomes prove that sparse feature usage provides a satisfactory output of about 91% in land cover/ land use classification [16].

Chong et al. [4] proposed a high determination satellite image classification technique utilizing morphological segment investigation of texture and cartoon layers. The sparse dictionary development as a part of the technique depends on the autonomous patch exploration. After the disintegration, the morphological coefficient vectors are acquired in both texture and cartoon layers, named the original multispectral satellite image's sparse nature. By consolidating the elements from two layers, the objective image classification's aggregate likelihood is figured out as indicated by the most extreme probability system [17]. The quantitative examination of test results and correlations with exemplary image classification calculations has demonstrated that the proposed classification technique has better accuracy, proficiency, and execution than most of the best classification strategies, provided the system is very complex.

Perumal and Bhaskaran [5] proposed land cover classification for multispectral remote sensing images with LISS III sensor based on Support Vector Machine. This paper compares several classifiers' performance and concludes that the Mahalanobis classifier performs better and achieves a classification accuracy of 85%. The algorithm produces accurate results, but the time consumption required is more.

Madhubala et al. [6] have classified the LISS III satellite images using Back Propagation Neural (BPN) network with five features in the feature set. Accuracy has been calculated for each output; the overall accuracy is 56%.

Nagarajan and Poongothai [7] studied the impact of changes in land use/land cover of Manimuktha sub-watershed of Vellar basin. The relationship between land-use changes and its trend is analyzed using IRS IC LISS III images. But they reached the Kappa coefficient to about 0.7, which is a moderate result.

Panchal et al. [8] have proposed the Modified Biogeography Based Optimization (BBO) calculation to order the regular landscape features and evaluate the qualitative result in Habitat Suitability Index. This scheme works on aerial photography and does not undergo high-resolution images. In this technique, the social species' ecological area is changed according to their livelihood atmosphere and surroundings. Here, the image's pixels were considered social species and land cover features like the natural living conditions (i.e., HIS file). These parameters are better than the other classifiers, and the product is 0.6715 was selected using the Kappa Coefficient. The feature extraction by different rules is utilized for classification. The ACO is used for feature extraction as Ant-Miner procedures [15].

Panchal et al. [9] have projected the combination of bio-inspired methods for land cover classification in remotely sensed images. In this paper, bio-inspired methods such as Biogeography Based Optimization (BBO) and Ant Colony Optimization (ACO) are incorporated, making the system very complex. Initially, the BBO method is implemented to extract land cover features and then tried with the ACO algorithm. The outcome turned inadequate for real-time implementations using the BBO technique and reached the

classification accuracy of about 78%. The concept of BBO works on only water pixel extraction, whereas ACO gives more exact outcomes while extracting more land features. Hence this paper has the limitation that ACO combined with a classifier produces optimal results than individual operation.

Johal et al. [10] have presented the theory of Flower Pollination by Artificial Bees with the BBO for the satellite images. In this technique, the FPAB do the groups of the pixels of the satellite image.

Gupta et al. [11] have presented a technique based on the living cells' biotic parts for satellite image classification. Here the Membrane Computing based optimization technique is introduced. The internal layer of the membrane contains membrane elements, whereas the outer layer is placed empty. Therefore, the pixels of the image to be classified are placed under the inner layer whose features are extracted, and classification was performed. The system produces about 85% accuracy with less reliability.

Goel et al. [12] proposed a new concept hybrid with both Fuzzy and BBO techniques. Also, Goel presented a hybrid ACO with BBO technique, and the results of both are compared. The Author also introduced the hybrid of Self-Organizing Feature maps and Ant Colony Optimization algorithm. The hybridization technique introduced here mainly focuses on high-resolution image classification. A novel method is also proposed to update the ACO technique to improve the results [14]. They compared all the optimization techniques and concluded with ACO, the best optimization technique compared with BBO and SOF.

Goel et al. [13], in their paper, proposed the combination of BBO with a binary value in terms of Digital Number (DN) introduced for land cover/land use classification. Here entropy is considered in feature extraction. It is found that the accuracy is inversely proportional to the entropy of land features of a selected area in choosing all spectral bands into consideration. The accuracy is reduced when features other than entropy is considered [15].

2.1 Summary

To classify urban land cover types, a variety of classification methods has been reviewed. However, several significant limitations have been found based on literature review: (1) some ways required prior knowledge on the study areas; (2) the processing time was not satisfactory; (3) some methods involved complex computational structure and required a large number of training samples; (4) some of them showed poor accuracy performance. The conclusion that in the existing algorithms, it is found that the misclassification rate is

high with high computational processing time and less efficiency.

3. Optimized RVM

The proposed modified probabilistic based RVM classifier algorithm has been implemented, and the classification results were observed in the previous module of this research. The modified RVM was implemented initially as an extension of the SVM classifier and produced satisfactory results. The performance can be further enhanced by optimizing the RVM kernel width parameter. The Ant Colony Optimization (ACO) technique is best suited to optimize the kernel width parameter of RVM and is called the Optimized RVM. The ACO algorithm's attitude is to determine the shortest route between the food source and their nest. An optimistic result can be yielded using ACO because of its parallelism and distributional features [10]. The ACO technique is chosen to optimize the parameters of the proposed modified RVM, which results in the state-of-the-art technique for all kinds of multispectral satellite images.

Different benchmark satellite images are considered for the experiment to evaluate the classification results of the proposed method. The experimental outcomes prove the efficiency of the proposed ACO-RVM in multi-class land cover classification with satellite images compared with conventional RVM. The experimental validation also produces the best classification results than other techniques. The methodology of the proposed ACO based optimized RVM is explained in Fig.1

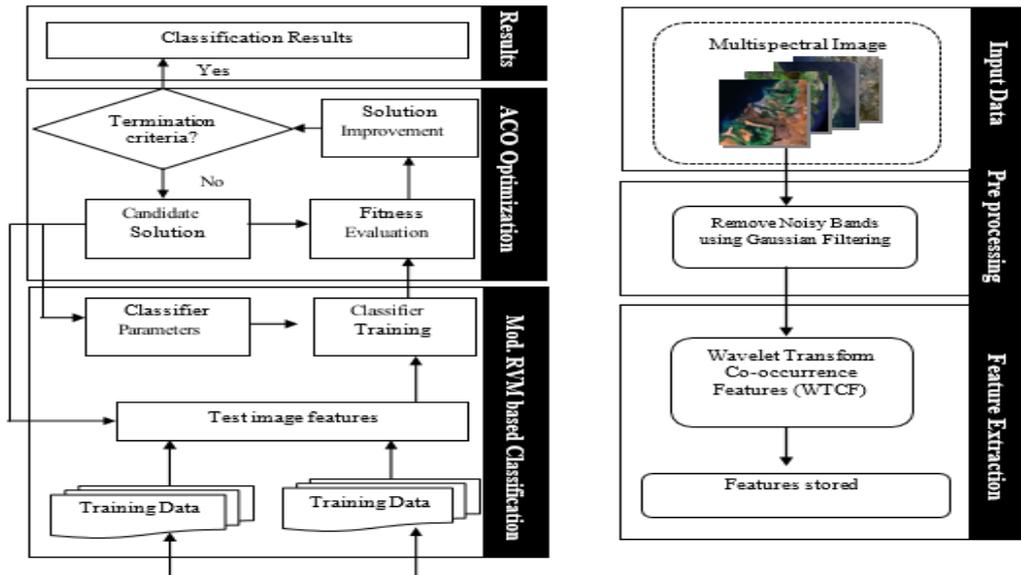


Figure 1. Flowchart of the Steps Involved in Proposed Optimized RVM Classification Scheme

3.1 The Proposed ACO Algorithm for Parameter Optimization of RVM

ACO works well in various optimization problems. The ACO technique is adopted for parameter optimization in the SVM algorithm [102, 103]. But the obtained classification accuracy is not satisfied. Hence, this research adopts the ACO based optimization algorithm to optimize the width parameter of the RVM and hence called the ACO- RVM classifier model for land cover mapping problem. The ants or the target class pixels are taken into account during each iteration, where the kernel width gets updated according to the optimistic pheromone trail. Finally, the RVM model performs the classification task with the obtained optimal parameter values.

(i) Objective Function for Parameter Optimization

The optimized procedures are utilized for optimizing the parameter of RVM, which is the ultimate aim. The parameter is optimized and updated in the objective function of RVM that minimizes the generalization error. It is estimated that the variance gets reduced as the size of the training set increases.

3.2 Land Cover Classification Using Modified RVM

The RVM is modified based on the Bayesian approach, where sparse nature is attained using the sparse distribution of the weights in a weight matrix. The accurate prediction of target t depends on the function $y(x)$ at some arbitrary

point x_i . Let's consider the training set comprised together with training inputs $X = \{x_1, \dots, x_N\}$ along

At some specific training points, the accurate prediction of a target t_i is based on some function $y(x)$, and the i^{th} target is defined as,

$$t_i = Y(X_i) + \varepsilon_i \tag{1}$$

In equation 1, ' x_i ' refers to any training point of the search space of $X = \{x_1, \dots, x_N\}$, $N=15$

At linear condition, the unknown test function $y(x)$ is a linear combination of some known kernel function $\phi_i(x)$ as in equation 2.

$$Y(X) = \sum_{i=1}^N w_i \phi_i(x) \tag{2}$$

where $w = (w_1, w_2, \dots, w_N)$ represents the linear combination of weights. Equation (1) can then be rewritten as:

$$t = \phi W + \varepsilon_i \tag{3}$$

The small values of weights were preferred, which leads to an appropriate smooth even function estimation and can be indicated by assigning a zero mean, Gaussian distribution to the weights:

$$P(W) = N(W|0, \sigma I) \tag{4}$$

Here, based on the probabilistic learning model, the variance parameter σ is modified to produce a precise classification output. Equation 3 can be modified to obtain the sparse weight probability distribution and given by,

$$p(w|\alpha) = \prod_{i=1}^N N(w_i|0, \alpha_i^{-1}) \tag{5}$$

To match the target on the training inputs from the search space, a learning model is studied so that the targets t_i can be accurately assigned for all set X inputs. The input vector x_i of X is obtained as per the explanation given in section 3.5.5. Generally, these allotments depend on the

function $y(x)$ expressed over the search space is represented as,

$$y(x; w) = \sum_{i=1}^M w_i \phi_i(x) = w^T \phi(x) \quad (6)$$

where $y(x; w)$ is the set of kernel basis functions. For a particular training point 'i' with a kernel function ϕ_i the above equation can be rewritten as:

$$y(x; w) = \sum_{i=1}^M w_i \phi_i(x - x_i) \quad (7)$$

The state updating rule is executed when all the ants have finished finding their solutions. The more pheromone deposited by the ant that gives the best solution is selected. Now the paths are updated by this pheromone amount new $\tau_{ij}^{old} +$ defined by the state updating rule given by,

$$\tau_{ij}^{new} = (1 - \rho)\tau_{ij}^{old} + \frac{Q}{e^T} \quad (8)$$

Q is the pheromone intensity and of ACO given by,

$$\text{Minimize } T = 1 - \frac{TP}{TP+FN} \quad (9)$$

where TP and FN represent the number of true and false classification training samples.

The state updating rule provides maximum pheromone, which produces the best solution set with very few classification errors.

$$f = Q \times \text{Accuracy} + (1 - Q) \times \frac{1}{N_f} \quad (10).$$

3.3 Gene Ontology Enrichment Analyses

Characterizing the complicated data of biological systems, such as DNA sequencing, without the aid of computational software or tools is a challenging task. Biological systems are very complex and require trust in computers represent knowledge.

The gene ontology (GO) task is a key bioinformatics initiative to enhance a computational representation of our evolving knowledge of how genes encode biological functions at the tissue system, cellular and molecular levels. The GO resource plays an important role in assistant biomedical research, including analyzing biological knowledge computation and interpretation of large-scale molecular experiments [18].

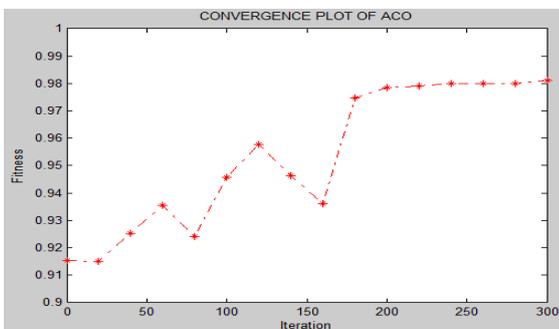


Figure 2. Convergence Plot of Fitness Value in ACO

4. Result and Discussion for the proposed system

The kernel parameter is optimized by using the ACO technique and updated in the objective function of the RVM classifier. The classification results by the optimized RVM classifier depends upon the fitness value for the number of iterations. The Ant-Miner transition rule's default parameter settings are Number of ants = 180, maximum iterations= 300. The experiment indicates that the parameters like the number of ants and the iterations are the two most sensitive factors determining the classification results. The classification results improve with the increase in the number of ants. The results stabilized accuracy improvement after the number of ants reaches 180. The program stops when the number of iterations is larger than the maximum iterations set as 300, which is the threshold. The values for the different ACO parameters are listed in Table 1.

Table 1. Parameter Values of ACO Algorithm

Sl.No.	Parameter	Value
1.	Evaporation Coefficient ρ	0.2
2.	Pheromone Intensity Q	100
3.	Maximum iterations	300
4.	Number of iterations at optimum	180
5.	The error of optimal solution e	0.002
6.	Optimized kernel parameter of σ	0.5

Fig.2 depicts the convergence plot for the ACO algorithm, and Fig.5.6 indicates the influence on accuracy over several iterations carried out. The fitness value is obtained from Fitness Value Vs. The number of iterations with evaporation coefficient ρ set to 0.2. The plot shows a better convergence behavior, and it also reaches a higher accuracy with fewer iterations. To reach the same accuracy, other optimization methods require significantly more iterations. The fitness value is valued as 92%, and from this evaluation, it is concluded that the proposed ACO method discovers an optimum value for the RVM parameter within a few iterations [19].

Fig. 3 demonstrates no sensitive discrepancies in the classification accuracy obtained and in determining the fitness value using the ACO optimization technique.

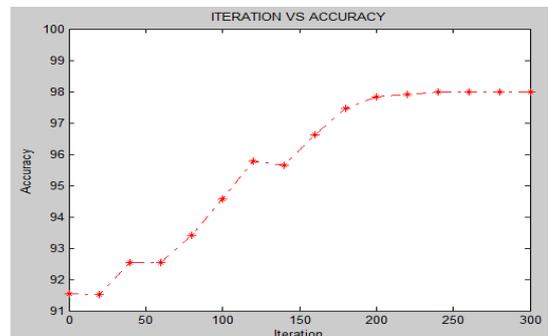


Figure 3. Influence Over Number of Iterations on Accuracy in ACO

It is shown that the fitness value is 0.97 obtained when the ants reach the earliest iteration level of 180. This is a good attempt when compared with other optimization techniques used for classifier parameter optimization. Also, the optimization algorithm's accuracy is considerably good at about 98 % at the same iteration level.

4.1 Classification Result

Experiments were conducted using the proposed ACO-RVM classification algorithm, and the classification results for the three sample images were shown in Fig. 4. The classified output images were observed for all the inputs for comparison purposes. The accuracy of the land mapping for all the three-satellite imagery was improved more by optimizing the proposed modified RVM classifier, i.e., the ACO-RVM classifier. In Fig 4, an (i), b(i), and c(i) represent the satellite images captured at Mumbai, the coast of Persian Gulf, Abudhabi, and Port, Macquarie, Australia, respectively. These input images are processed and obtained the classified image outputs. The obtained classification outputs for all the three multispectral satellite images make clear that the proposed Optimized RVM Classifier performs better. The proposed Optimized RVM Classification technique's performance evaluation is analyzed based on the confusion matrix as in previous modules. The performance measures like overall accuracy, kappa coefficient, sensitivity, specificity, and error rate were evaluated from the obtained confusion matrix developed from the image classification results.

Table 2 (a-c) and Table 3 (a-c) shows the confusion matrix and accuracy indices obtained respectively using the proposed ACO based Optimized RVM classifier for three different satellite images. From the confusion matrix tables, the overall accuracy for the three classified output images is determined as 99.19%, 99.97%, and 98.01%, respectively. Similarly, the Kappa Coefficient results are obtained as 0.9814, 0.9997, and 0.9521 respectively.

Table 2. Confusion Matrix Obtained Using Proposed ACO-RVM Classifier

a) Confusion Matrix for Satellite Image of Mumbai

Class	Building	Vegetation	Water	Land	Total
Unclassified	0	0	0	0	0
Building [Red]	2606	0	0	50	2656
Vegetation [Green]	0	3972	0	50	4022
Water [Blue]	0	0	5356	16	5372
Land [Yellow]	0	0	0	2290	2290
Total	2606	3972	5356	2406	14340

b) Confusion Matrix for Satellite Image of Coast of Persian Gulf, Abu Dhabi

Class	Building	Vegetation	Water	Land	Total
Unclassified	0	0	0	0	0
Building [Red]	1434	0	0	1	1435
Vegetation [Green]	0	463	0	0	463
Water [Blue]	0	0	1559	0	1559
Land [Yellow]	0	0	0	1286	1286
Total	1434	463	1559	1287	4743

c) Confusion Matrix for Satellite Image of Port Macquarie, Australia

Class	Building	Vegetation	Water	Land	Total
Unclassified	0	0	0	0	0
Building [Red]	1478	5	0	1	1483
Vegetation [Green]	24	1189	8	0	1221
Water [Blue]	0	2	1030	20	1052
Land [Yellow]	20	0	0	200	220
Total	1522	1196	1038	220	3976

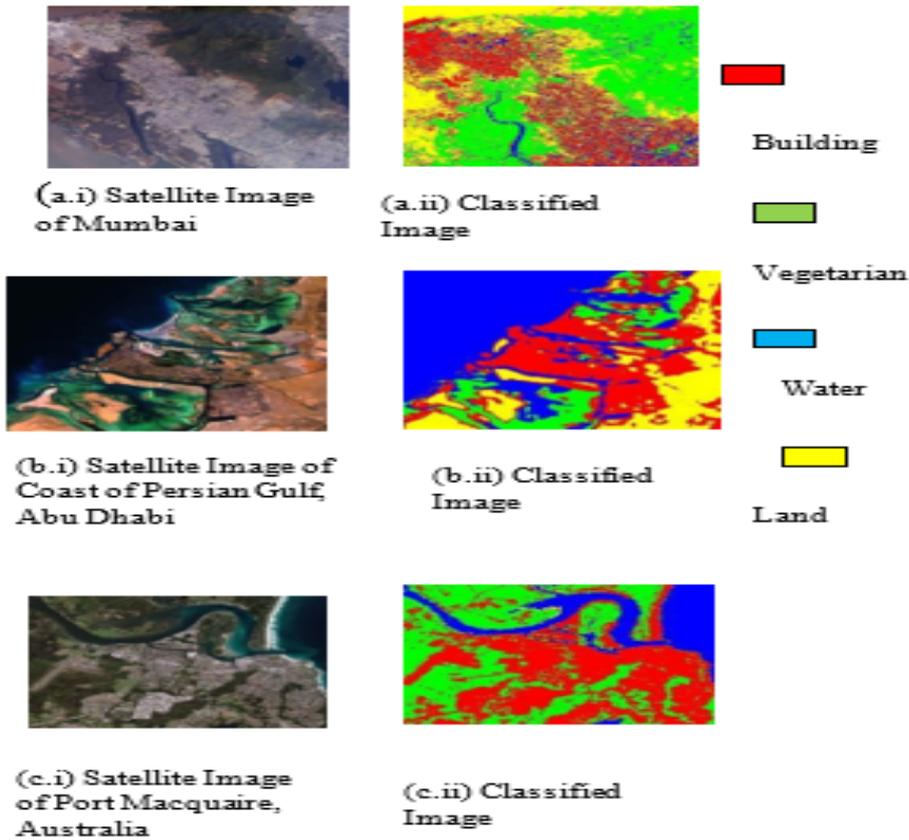


Figure 4. Classification Results Using the Proposed Optimized RVM Classifier

Table 3. Accuracy Indices Evaluated Using Proposed ACO-RVM Classifier

a) Accuracy Indices Evaluated for Satellite Image of Mumbai

Class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Building [Red]	100	98.12	2606/2606	2606/2656
Vegetation [Green]	100	98.76	3972/3972	3972/4022
Water [Blue]	100	99.7	5356/5356	5356/5372
Land [Yellow]	95.18	100	2290/1287	1030/1052
Overall Accuracy = (14224/14340)99.19%				
Kappa Coefficient = 0.981				

b) Accuracy Indices Evaluated for Satellite Image of Coast of Persian Gulf, Abu Dhabi

Class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Building [Red]	100	99.93	1434/1434	1434/1435
Vegetation [Green]	100	100	463/463	463/463
Water [Blue]	100	100	1559/1559	1559/1559
Land [Yellow]	99.92	100	1286/1287	1286/1286
Overall Accuracy = (4742/4743)99.9789%				
Kappa Coefficient = 0.9997				

c) Accuracy Indices Evaluated for Satellite Image of Port Macquarie, Australia

Class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Building [Red]	97.11	99.66	1478/1522	1478/1483
Vegetation [Green]	99.41	97.38	1189/1196	1189/1221
Water [Blue]	99.23	97.91	1030/1038	1030/1052
Land [Yellow]	90.91	90.91	200/220	200/220
Overall Accuracy = (3897/3976)98.013%				
Kappa Coefficient = 0.9521				

The various performance measures proved that the proposed ACO-RVM classifier works better with improved classification accuracy than the state-of-the-art KNN, MSVM, Sparse MSVM, and modified RVM based classifiers.

5. Conclusion

The working and implementation of the proposed modified RVM and ACO based Optimized RVM were discussed. The classification results involving different urban land classes from test multispectral satellite images were also discussed. The kernel parameter of RVM was initially optimized through the Ant-miner transition rule for the Gaussian RBF kernel using the ACO optimization algorithm. The parameter setting was fixed during the features training phase and performed classification by the Optimized RVM classifier. Finally, the classification results of the methods are discussed based on various performance indices. From the confusion matrices for all the input satellite images, namely satellite image of Mumbai, a satellite image of the coast of Persian Gulf, Abu Dhabi, and the satellite image of port Macquarie, Australia, it is seen that the land classes are classified correctly with overall accuracy values of 99.19%, 99.97%, and 98.01% respectively.

In contrast, the Kappa Coefficient values are obtained better as 0.9814, 0.9997, and 0.9521, respectively. These qualitative results find more improvement as compared with previous classifier results. In the future, the Fourier Descriptors, Moment-Based Features, Hierarchical Centroids, and Histogram of Oriented Gradients algorithm have used for extraction of images from datasets.

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