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Research Article

Satellite Image Classification Using HMM with Whale Optimization

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Abstract

The purpose of this paper, the proposal a new method that combining the Hidden Markov Model (HMM) and Whale Optimization together in remote sensing to resolve the land cover issue by splitting the unsupervised satellite image using threshold value. The HMM helps in extraction of texture modeling and segmentation such as classification. The majority of the model contextual dependencies and the absorption of noise. To test the proposed method a very high resolution remote sensing image was used, acquired by a world view - 4. The results show the best performance of the proposed method related to the problem through image segmentation. The processing time is low in relative with the faster convergence. Results of experiment specify that HMM-WOA generates higher precision than the existing method. Therefore, it gives an unsupervised effective algorithm for the remote sensing image of classification.

Index Terms - *Hidden Markov Model (HMM), satellite image classification, whale optimization (WOA).*

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Introduction

Images of higher resolution provides ground details of a high level and are capable of capturing objects in narrow or small in sizes like trees and foot paths. Subsequently, it acquires VHR images in large numbers for various applications in real life including land supervision, urban monitoring and change detection. The idea of satellite picture characterization bunches the picture pixel esteems in the significant classes. Distinctive satellite picture grouping systems are accessible. It very well may be extensively arranged in three classes specifically, manual, programmed and crossover. All made reference to strategies have their very own points of interest and in addition impediments. A large portion of the groupings are considered in introductory classification. Satellite Image arrangement requires correct grouping choice based on the prerequisites. The idea of picture arrangement builds up the clarification of center for land cover mapping issue. The arrangement of satellite pictures has end up being a functioning examination territory in the field of picture preparing. Correct capabilities of pictures are required for any kind of order. There are number of groups existed in single information and the element extraction from assortment of groups is troublesome. The information for the grouping is not compelling after the execution, along these lines, the advancement is important of the capabilities.

The developing creations of maps are producing colossal volumes of information that surpass individuals' ability to examine them in addition these informational indexes have diverse assets and sorts. It appears to be suitable to apply information disclosure techniques like information mining to spatial information along these lines, a standout amongst the most critical application in spatial information digging is to detect remote pictures. The extraction of spatial information is an outstanding field of application for spatial information measurements have been compiled in different types ranging from remote management to geographic information systems (GIS). The information gathered has far exceeded the human capacity to investigate it.

The symbolism of the various satellites offers a huge source of spatial information. Remote symbolism can be used in various applications including geology, urban organization, growth control and soil assessment [8], In general, remote sensing provides the basic inclusion, mapping and grouping of the highlights of land cover. One of the most important uses of information that are remotely sensed is to create a channel to the characterization of important or identifiable important aspects or land cover classes that are composed in a scene. [9]. In this way, the vital element is a topical guide with themes such as land, topography and vegetation. [10].

Picture arrangement is the way toward doling out pixels of a picture to recognize classes and is considered as imperative device to explore and examination computerized pictures so Choosing an appropriate order procedure is considers as critical job for deciding the nature of grouping results. Picture grouping dependent on remote detecting has an incredible impact since numerous applications in various fields as natural, financial rely upon that order result [11]. Characterization, as a major piece of regulated learning issue, has dependably pulled in heaps of consideration for its different applications. Likewise, numerous techniques are presented to handle this issue.

Statistical approaches control probabilities and also endeavor in displaying the whole space of hypothesis and information conveyance utilizing probabilities dispersion thickness, therefore giving more total portrayal of the genuine issues; be that as it may, it additionally requests enormous multifaceted nature to accomplish the objective. Gaussian mixture model performs order by removing worldwide insights from Gaussian distribution of pixel power in a picture informational collection. GMM is particularly for parameter estimation and grouping.

In this study we have used hidden Markov (HMM) models for the clustering of uncontrolled satellite images. The HMMs have been widely and effectively used for the demonstration and division of the surface (i.e., the layout), this is significantly due to their ability to show logical conditions and retention of concussion [12]. Land cover is a variable to vital geospatial for the human and physical conditions of the concentrate and is progressively used as informational information in unambiguous ecological spatially and natural models, ranging from global environmental change to definitive research on soil erosion [13].

Among the most recent decades, new sensors and effectively open information documents have expanded the measure of accessible remote detecting information. This improvement requires hearty, transferable and computerized techniques and preparing administrations for induction of precise data that can be delivered inside a brief time frame [14].

This study paper is presented as below. Related work is presented in Section II. Section III states methods that exist. Section-IV represents the details of proposed method. Section V reports the used VHR image, experiment results and its analysis. Section VI infers the conclusion.

Related Work

Jesus et. al [15] describes ontology about the supervised ocean satellite picture arrangement technique. This technique shows intensity of metaphysics in sea satellite picture order. The strategy extricates low level highlights from sea satellite pictures and speaks to in owl record design. This owl document is converged with space ontologies and marking rules. Xingping Wen et al [16] proposed a method called the unsupervised classification method. The first shows the hyper spectral remote sensing image, with atmospherically collection. Exactness environmental amendment is the way to the grouping. At that point, end part spectra were extricated utilizing PPI calculation, and the picture was grouped utilizing SAM. Customarily SAM calculation utilized consistent limit. They have improved and used the moving edge, and the pixel has a classy place that has the smallest phantom edge. Finally, the spectra of the final part were grouped according to the K mean calculation and the classes were joined by the result of the K-implies calculation. The last scheme of the anticipated and assigned characterization. It is a viable strategy, particularly for the extremely supernatural remote sensing image. Customers can also change the final part and the number of classes based on their usages.GMM which refers to Gaussian mixing models are generally used for unattended characterization usages in remote sensing. EM referring to Expectation maximization is the general calculation used to calculate the parameters of these models. However, such iterative advancement techniques can undoubtedly be trapped in close neighbors. Scientists use stochastic search calculations based on popularity to acquire better calibers.

Omar S. Soliman et al. [17] presented a characterization framework for the remote sensing of ASTER satellite symbolism using the (SVM) support vector and the calculation of particle swarm optimization (PSO). The recommended structure starts along the distinctive test of the chosen study area. It is followed by an early preparation phase that uses the calculation of the polynomial mapping as an adjustment of geometric. Persecuted by, applying the edge calculation for image division. At that point, highlights are highlighted using object-based calculations. Persecuted by, grouping images using SVM and optimizing particle swarm (PSO). The OSP is used as a quick calculation of world progress instead of using conventional calculation, for example the conditions of Karush-Kuhn-Tucker. It would be updated and evaluated in the territory chosen by two authentic enthusiasms for the north-eastern part of the eastern desert of Egypt (Halaib triangle) and (Wadi Shait).

Francesca Bovolo et.al [18] used a new SVM-sensitive clustering procedure that uses remote sensing images. It has two fundamental properties used in a new approach: i) the SVM portion in characterizing a cost-sensitive adjustment work; ii) spatial configuration data in the disposition phase. The results provided by the context-sensitive SVM were contrasted and were achieved by a SVM sensitive to the standard context and the best system was found later. Yu Zhang [19] presents a particles' group. Every element lives in a situation in space of hunt and depends on a molecule swarm improvement and SVM systems utilizing Corel Image Database. SVM was discovered by them, BPNN which refers to Back Propagation Neural Network and also RBF which means to Radial Basis Function are used in contrast and PSO-SVM. The calculation comprises of these means, that have been rehashed till it reaches halting state. Initial step, assesses the wellness of every molecule as indicated by the coveted enhancement, second step refreshes nearby best wellness and worldwide best wellness and third steps refreshes the speed and position of the particles. Aguilar et al. [20] compared the potential of

VHSR images on urban coverage. The OBC was utilized to serve the purpose and the results were evaluated with multiple sizes of data pairs of training, various land cover and various feature sets.

Kavzoglu et al. [21] derived the joint learning algorithm's performance, i.e., a rotation forest in the OCE of an image of WV-2 satellite. For the reason, five combinations of characteristics were generated and the performance of the classification was investigated. Many researchers have been recorded concerning FS methods that use evolutionary calculation techniques in the literature of remote sensing. Gong et al. [22], we reiterated the information of fuzzy local algorithm of c-means cluster and implemented it in solving problem in detecting change of SAR (synthetic aperture radar) image. Along with, a approach of level set was utilized to change in detecting in imagery of multispectral and sensed remotely and gathered a acceptable result based on dividing DI into various scale.

Im et al. [23] suggested method of identification of change which is object-based with analysis of correlation image shared with segmentation technique of multi resolution and also attained accepted results. But, these approaches in general need be compatible in adopting way of trail-and-error in optimizing parameters in order to create important image objects, as there is not any algorithm which is suitable for all conditions. Because of the capability of producing regions of identical and homogeneous which save most useful information, technique of super pixel begins to be broadly used in detection of change and also classification of Hyper spectral image.

Existing Method

Existing strategy depends on the Gaussian Mixture Modeling (GMM) of the component vectors separated from the satellite picture and the particle swarm optimization (PSO) enhancement. The key commitment is the improvement of the GMM method show for each class dependent on the preparation information. A picture bunching strategy that depends on the particle swarm optimization (PSO). The calculation finds the driver of a client indicated number of bunches, where each group bunches together comparative picture natives.

GMM Algorithm

A Gaussian Mixture Model (GMM) is a density function with parametric probability expressed as density of the Gaussian weighted segment. GMM are in general utilized as a probability distribution of parametric model of dimensions or uninterrupted characteristics in a system of biometric, like the characteristics of spectral associated to vocal accent in systems of speaker identification. The parameters of GMM are projected from the data of training with the help of iterative algorithm of Expectations-Maximization (EM) or MAP which refers to Maximum Posterior estimate based on previous model which are well-trained. Every component density in form of Gaussian function is provided by

$$g(x|\mu_j,\Sigma_j) = \frac{1}{(2\pi|\Sigma_j|)} exp\left[-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu_j)\right] \quad (1)$$

Where mean vector μ_j and the covariance frameworkΣ_j.

The mixture density limitation is reached and specified by following form,

$\sum_{j=1}^{M} w_j = 1$ (2)

The vectors of mean, matrices of covariance and mixture weights based from densities of all components were applied for complete parameterization of Gaussian distribution. These parameters are jointly characterized by notation

$$\lambda = \{w_j, \mu_j, \Sigma_j\} \quad j = 1 \ldots\ldots M \quad (3)$$

In addition to this, to estimate the parameter we use the maximization of the expectation and the maximum likelihood. Specified vectors of training and a configuration of GMM, we would like to estimate GMM parameters, λ , which in a assured sense is best fit to training characteristics vectors distribution.

There are various methods existing to estimate GMM parameters and containing its own approach of estimation. Among the various accessible strategies, the settled and most mainstream method is MLE which is called as Maximum Likelihood Estimation.

In GMM, The weighted sum of Mixture component Gaussian densities as described by the following equation,

$$p(x|\lambda) = \sum_{j=1}^{M} w_j \; g\left(x \middle| \mu_j, \Sigma_j\right) \quad (4)$$

Where x is a data vector of continuous value in the dimension D (measurement of the characteristics), W_j, j = 1 ......, M, are the weights of the mixture and $g(x|\mu_j, \Sigma_j)$, and j = 1 .. .., M, are the Gaussian densities of the components.

To increase the possibility of the GMM provided the ML estimation of parameters of model is applied which would be superior in data of training. For a sequence of training vectors T $x=\{X_1....,X_T\}$, the GMM probability presuming freedom between the vectors 1 could be expressed as,

$$p(x|\lambda) = \prod_{t=1}^{T} p(x_t|\lambda) \quad (5)$$

Regrettably, this formula is a function of non-linear of parameters λ and hence maximization directly is not feasible. But, estimation of ML parameter could be iteratively gathered with the help of special condition of algorithm of Expectation Maximization which is EM algorithm. The new model which turns into the preliminary model to the subsequent iteration then the process repeats till it reaches convergence threshold. The first model is characteristically derived with the help of particular form of quantization of binary vector.

PSO

Particle Swarm Optimization which referred as PS is tool which is based on optimization of stochastic population where it relates to social behavior. PSO is on the basis of swarms' movement and intelligence. While using Particle Swam Optimization it computes to optimize problem and brings out peculiar candidates. The fundamental PSO concept is given in Figure 1 which lies to accelerate every particle to location of its specific best and global best. Candidate solution is dealt in this method and to attain input image quality, it can be enhanced.

Particle best

While using PSO, Particles having possible solution will fly in the space of problem and it follows current particle that provides solution near to optimum. These particles remain follow its coordinates connected with best optimum solutions. With the help of this method, the nearest fitness value can be accomplished. The achieved value is called as P_{bt}.

Local best

The best value which could be monitored by the PSO would be specific values of every individual in space of search. This location is referred as L_{bt}.

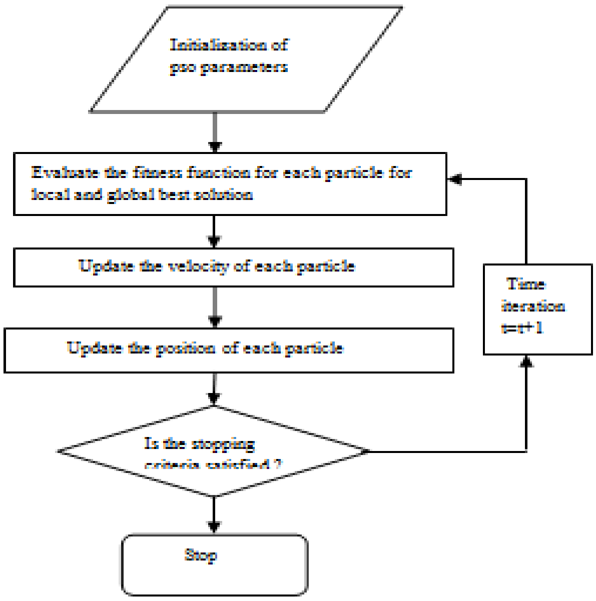

Figure 1. Flowchart for PSO

Global best

The mentioned particle contains the neighbors that are topological, the attained best values is mentioned asG_{bt}. To attain the preferred results, the histograms of various scenes in the database consisting of Objects, were examined. Based on analysis, with the help of unattended learning, the histogram is subdivided into five primary regions. Calculation t which is Threshold with the help of PSO the values of threshold are assessed and also ten agents are generated that scan their individual regions that is assigned to them from the picture. Image is scanned by each agent row wise to identify best local values for every row and finally assess its best global for predefined region. Among the regional and global bests the agents choose the most appropriate candidate result with the help of communication of one another. This is generally known as the Global best or Threshold value.

Proposed Methodology

This study would apply Hidden Markov Models which is called HMM to categorize the coverage of terrestrial from satellite images of multispectral and offer a new technique to sequence the image pixels (observations) to acclimatize them to HMM and attain the best categorization. With this, whale optimization is combined to achieve the best segmentation threshold.

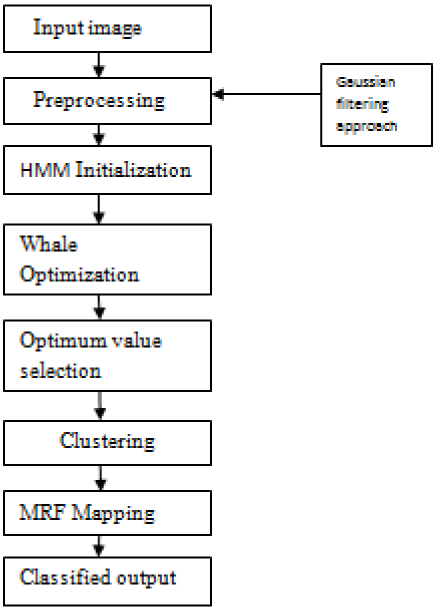

Figure 2. Block diagram of recommended method

Algorithm steps

Step 1: Load Input Satellite Image and find the total no. of rows and columns of satellite picture pixels and then preprocess image.

Step 2: Initialized the population and set the iteration using whale optimization method

Step 3: Train data for optimized data according to bands

Step 4: Finding best solution using the training for the classification image

Step 5: Classify water, vegetation, and urban, rocky as well as barren according to the trained data.

Pre-processing phase

The objective of preprocessing of digital image remote sensing is to maximize the accuracy digital data and its ability to interpret during the phase of image processing. Also, from satellites, imagery of remote sensing changes with respect to geometric distortions. Hence operations of pre-processing should be needed Gaussian filtering to get noise free image.

HMM Algorithm

An HMM is differentiated from a Markov model that, the states mentioned in an HMM could not be directly measured which is hidden and could be calculated only through a series of observations created along with a time series. Presume the total no. of states in HMM is N, and q_t and o_t specify system state and observation is at t time.

HMM could be properly defined by λ= (A_x, B_y, π), where A_x is a probability matrix of transition occurs between states, B_y is a observation matrix of probability densities associated with states, and π is a matrix of probabilities of initial state respectively.

Especially, A, B & π are every further described as below:

$A_x = [a_{ij}], a_{ij} = P(q_{t-1} = j|q_t = i), L \leq i, j \leq N$(6)

Where,

$a_{ij} \geq 0, \sum_{j=1}^{N} a_{ij} = 1, for\ i = 1, 2 \ldots N$(7)

$B_y = [b_j(o_{t-1})], b_j(o_{t-1}) = p(o_{t-1}|q_{t-1} = j), 1 \leq j \leq N$ (8)

$\pi = [\pi_i], \pi_i = P(q_t = i),\ 1 \leq i \leq N$

Where,

$\sum_{i=1}^{M} \pi_i = 1$ (9)

For the purpose of illustration, HMM model and its associated parameters are A_x, B_y and π. Given HMM, λ and sequence of observation O = {o_1, o_2,.., o_T}, best state sequence can be estimated Q* = {q_1, q_2,…,q_T} on the basis of method of dynamic programming which will result in maximizing P(Q*|O, l). To convert Q* meaningful, model parameters of A, B and π have to be set-up well. The Baum-Welch algorithm is the commonly applied methodology to estimate parameters of model. model parameters of A, B and π have to be set-up well. The Baum-Welch algorithm is the commonly applied methodology to estimate parameters of model.

The model parameters of p, a_{ij}, are described as

$$\pi = \gamma_t\,(i)$$

$\overline{a_{ij}} = \frac{\sum_{t-1}^{T-1} \xi(i,j)}{\sum_{t-1}^{T-1} \gamma_t(i)}\quad i = 1,2 \ldots . N$(10)

$\overline{b_j}(k) = \frac{\sum_{t-1,\ o_t=f_k}^{T-1} \gamma_t(j)}{\sum_{t-1}^{T-1} \gamma_t(j)}\quad j = 1,2 \ldots . N$ (11)

Where γ_t(i) specifies conditional probability of staying in i state at t time, provided observations, and ξ_t (i, j) is the conditional probability of transition which is from i state at t time to j state at t + 1time, provided the observations.

$\alpha_t(\,i\,) = \pi_i b_i(o_t)\ 1 \leq i \leq N$(12)

$\alpha_{t-1}(i) = b_i(o_{t-1}) \sum_{j=1}^{N}[a_i(i), a_{ij}], for 1 \leq t \leq T, for\ 1 \leq i \leq N$(13)

Let the probability of backwards b $_{t\,(i)}$ be probability of conditional to observe the sequence of observation O_t at T = {o_{t-1}, o_{t-2}, ..., o_T} after stated time of 't' as i represents the state at the time t.

To inductively solve probability of forward b_t (i), following formulacan be used

$$\beta_T = i \; 1 \leq i \leq N \tag{14}$$

$$\beta_{t-1}(i) = \sum_{j=1}^{N}[a_{ij} b_i(o_{t-1})\beta_{t-1}(j)],\; t = T+1 \; for 1 \leq i \leq N \tag{15}$$

The probabilities of γ_t (i) and ξ_t (i, j) are resolved as

$$\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{j=1}^{M}\alpha_t(i)\beta_t(i)} \tag{16}$$

$$\xi_t(i,j) = \frac{\alpha_t(i)a_{ij}\, b_i(o_{t-1})\beta_{t-1}(i)}{\sum_{j=1}^{M}\sum_{j=1}^{M}\alpha_t(i)a_{ij}\, b_i(o_{t-1})\beta_{t-1}(j)} \tag{17}$$

Whale Optimization Algorithm

The whale optimization algorithm is inspired by the hunting performance of humpback whales. Their hunting technique is referred as the bubble net feeding approach. The workflow of the whale optimization algorithm is shown in Figure 3. The whale has been defined in three ways. 1. Around the prey, 2. Method of attack of the net of bubbles, 3. Search for a prey.

Around the Prey

The adjustment in position with regarded to the current best arrangement alternate whales used to refresh its position utilizing following condition.

$$E = | B \odot X_1^*(t_1) - X_2(t_1) | \tag{18}$$

$$X_2(t_1+1) = | X1^*(t_1) - C \odot E | \tag{19}$$

Where E is the distance vector represents the distance of current whale position from the best whale position, $t_1$indicates present iteration. C and B denotes coefficient vectors. X_1* is the position vector of the best solution and then X_2 refers to position of a solution, The symbol | | denotes the absolute values. The vector C & B are computed as stated below

$$C = 2a_1 \odot r_1 - a_1$$

$$B = 2.r_1$$

Where components are linearly decreased from 2 to 0 over the course of iterations and r_1 is random vector in [0,1].

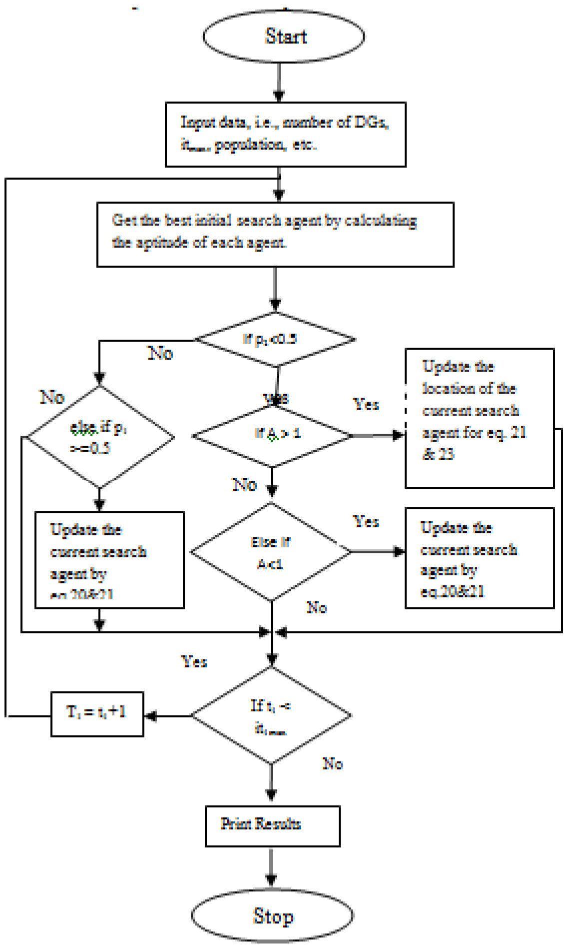

Figure 3. Flowchart of Whale Optimization Algorithm

Bubble-Net Attacking Method

Whale hunts their prey in 2 ways. One is shrinking encircling mechanism which has been explained above. The other one is spiral updating position. In spiral updating position the whales do not exhibit a discontinued circle between its current and predecessor position.

There exists a continuous path which resembles a spiral. If this manner is applicable in hunting prey, then the above equation can be rephrased as shown below.

$X_2(t_1+1) = E' \odot e^{bt} \odot \cos(2\pi l) + X_1^*(t)$ (20)

Here $E' = |X_1^*(t) - X_2(t)|$ is the distance of prey from the whale, b is a constant to determine the logarithmic spiral's shape, $\odot$ is multiplication of element by element, and l refers to random value [−1, 1]. The probability as encircling shrinking mechanism and the other half as spiral update position in exploitation phase. So the algorithm has been modelled as

$$X_2(t_1+1) = \begin{cases} X_1^*(t) - C \odot E & \text{if } p_1 \geq 0.5 \\ E' \odot e^{bt} \odot \cos(2\pi l) + X_1^*(t) & \text{if } p_1 < 0.5 \end{cases} \quad (21)$$

where random number [0, 1] is denoted by p_1.

Search for Prey

Prey search is a process of exploration. Many optimization algorithms incorporate this exploration phase in different format. Exploration is the process of accessing new search space or to deviate the guided search towards a random search. This leads to exploration of new search space which then can be used to exploit best solutions in the upcoming iterations.
In whale optimization, exploration mechanism has been defined as follows

$E_P = |\, B \odot X_{rand} - X_2(t_1)|$(22)

$X_2\,(t_1{+}1) = |X_{rand} - C \odot E\,|$(23)

X_{rand} refers to current iteration's random whales. | | denotes the absolute value.

Performance Measures

Performance is measured with four factors: Accuracy, kappa value, NAE and NCC.

Accuracy:

This method is widely applied statistic to validate. Percentage of Misclassified pixels present in the image represents the accuracy and it is expressed as

$$p_o = \frac{\sum_i n_{ii}}{n} \quad (24)$$

Kappa index:

This method of measure is same as overall accuracy; however it introduces an agreement of chance. A value of zero refers that classification agrees to reference as poor as an aleatory classification. Following formula is used to compute the kappa index

$$K = \frac{n\sum_i n_{ii} - \sum_i n_{i+} n_{+i}}{n^2 - \sum_i n_{i+} n_{+i}} \quad (25)$$

Normalized Absolute Error:

This measure of quality shall be articulated as below.

$$NAE = \frac{\sum_{i_t=1}^{m}\sum_{j_m=1}^{n}\left(|A_{i_t j_m} - B_{i_t j_m}|\right)}{\sum_{i_t=1}^{m}\sum_{j_m=1}^{n}\left(A_{i_t j_m}\right)} \quad (26)$$

A higher NAE value indicates that the image is of low quality

Normalized Cross Correlation:

The measurement of NCC states the relationship between the processed and reference image. NCC is explained as follows.

$$NCC = \sum_{i_t=1}^{m}\sum_{j_m=1}^{n} \frac{\left(A_{i_t j_m} \times B_{i_t j_m}\right)}{\mathbf{A^2}_{i_t j_m}} \quad (27)$$

Experimental Results

Area of studyand data used

To verify the effectiveness of proposed method we select data obtained by high resolution satellite images. The high dimensional satellite images captured by WorldView-4. input image used in this study is of sao Paulo in brazil recorded on December 29, 2016 shall be considered by the Indian satellite with remote sensing world view-4. the world view-4 providing panchromatic of 31cm and 1.24 meter (m) band of four multispectral which are blue, green, red and near-infrared. The maximum resolution of 30 cm. the land cover characteristics of images applied in research involves procedure of wasteland, urban, water body, vegetation & hilly region.

Simulation Results of GMM-PSO (Existing)

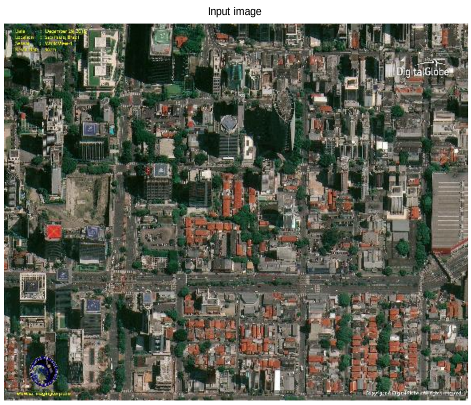

Figure 4. Input image

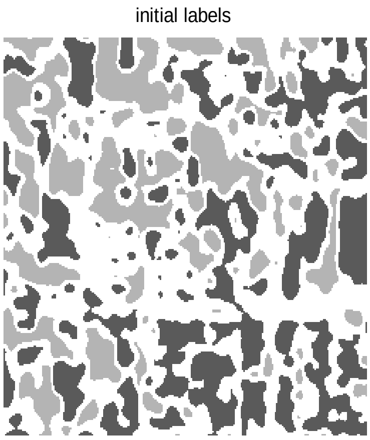

Figure 5. Initial labels of input image

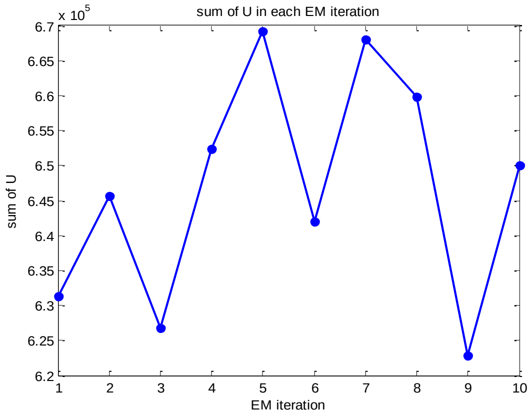

Figure 6. EM Iteration

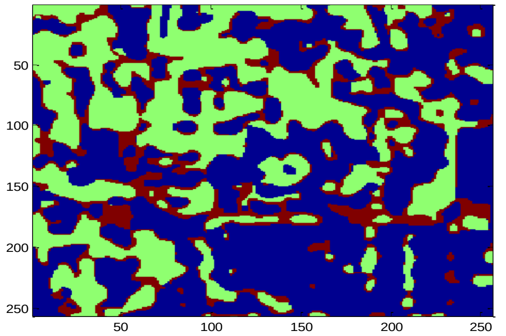

Figure 7. Labels after classification

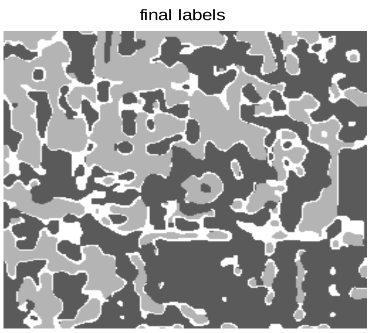

Figure 8. Final labels

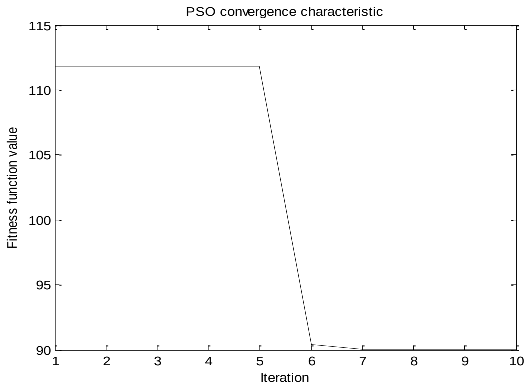

Figure 9. PSO convergence graph

Simulation Results 0f HMM-WAO (Proposed)

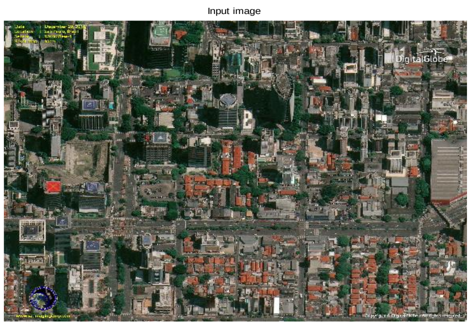

Figure 10. Input image

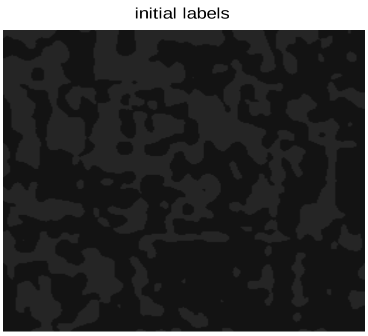

Figure 11. Initial labels

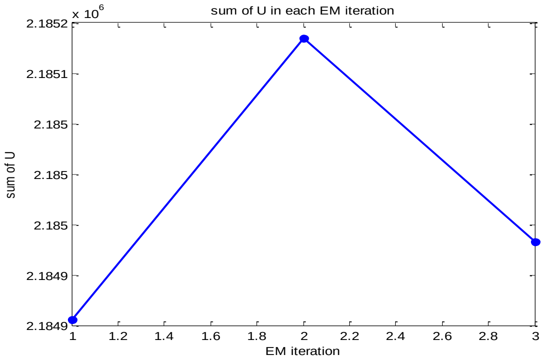

Figure 12. EM Iteration

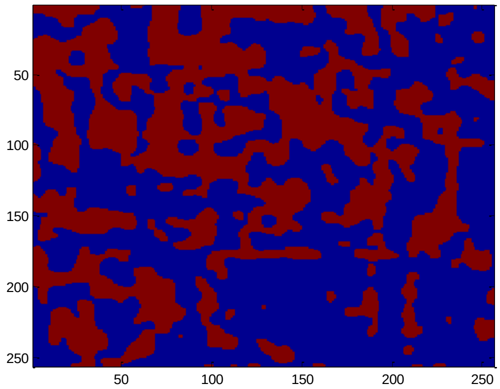

Figure 13. Labels after classification

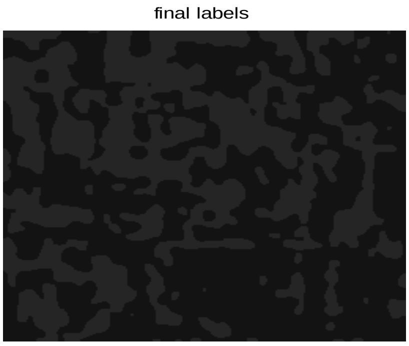

Figure 14. Final labels

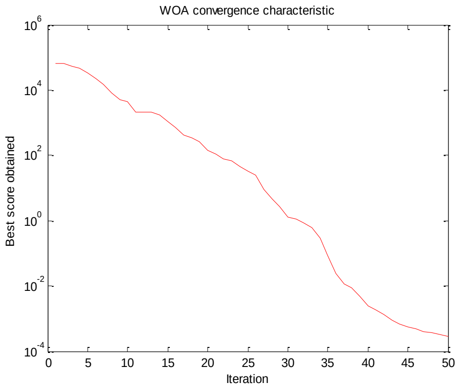

Figure 15. WAO convergence graph

Table 1 Performance comparison of GMM-PSO and HMM-WOA

Methods	Accuracy	Kappa values	NAE	NCC
Existing (GMM with PSO)	87.9	0.8388	5.913299e^{-01}db	4.633293e^{-03}
Proposed (HMM with WOA)	98	0.9674	7.98165e^{-03}db	1.42877e^{-03}

Conclusion

The primary approach of analysis that is used in this paper is HMM, which involves study of change of land cover in the area of study hence it gives city planners' information. HMM with Whale optimization have been recommended and established in quality of visual via classifications that are unattended. In this study, the recommended techniques are implemented to remote sensing images. The proposed methods are useful to greater resolution imagery that is sensed remotely which results in better accuracy and increased quality in visual.As with any new approach, there are some unresolved issues that may present challenges in due course. One of the most important challenges is the type of image; WV-4 images have been used in this paper, while different types of images, such as aerial images, could be considered and evaluated.

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