International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 8 (2018) pp. 5736-5744

Mixed Pixel Classification by Using Hybridization of Evolutionary Method With Neural Networks

Sumit Kaur[a] and Dr. R.K Bansal [b]

[a]*Research Scholar, Gurukashi University, Talwandi Saboo, India*

[b]*Dean Research, Gurukashi University, Talwandi Saboo, India*

Abstract

The images obtained from satellite gives the necessary data about the geographical condition and variations of the earth. It helps in the reduction of time while working in the field because images obtain from the satellite gives the relevant data which is full of quality and quantity. As the main focus of our work is on the classification of images obtain by satellites, satellite image classification is a strong technique which is used for the extraction of informative data. In each remotely detected image, an extensive number of mixed pixels are available. In this work, the labeling of mixed pixel is done by using hybridization of PFCM and BBO. PFCM algorithm used to form clustering to speed up the process and Biogeography-Based Optimization is used for the classification of super mixed pixels. The performance evaluation of the proposed work is improved in terms of parameters that are TP rate, FP rate, Precision, Recall, F_measure, and accuracy. The overall accuracy of this work is 96.1 and RMSE is 0.032607.

Keywords: Satellite images, mixed pixels, FCM, PSO, BBO

INTRODUCTION

Remote sensing is a science of extracting information from an area without being in direct physical contact with it. Remotely perceived knowledge, akin to satellite pictures, area unit measurements of mirrored radiation, energy emitted by the world itself or energy emitted by microwave radar systems that's mirrored by the world. Remote sensing becoming very popular in various fields (e.g. agriculture, defense, environment studied, etc., mention in table 1.1) and make feasible to acquire and analysis the area of earth and space which is not possible by human to be there direct physically. Information will be achieved from remote sensed images by using image classification. The classification operation of remotely sensed imaged depends on ground data, means that the area under study is the mixture of number of unique but internally homogeneous classes which can be differentiated by using ground data, reflectance and ancillary data[4][2]. While when dealing with remote sensed images the main focus is to find the fractions of diverse coverages in an area. To get more accurate result high resolution satellites are also used but such assumptions are not valid in region having fuzziness, which occurred due to the presence of mixed pixels. RS image consist of two types of pixels; pure pixels which represent single class and mixed pixels which consist heterogeneous properties for more than one class. Mixed pixel arise because the pixel length may not be pleasant sufficient to seize element at the ground essential for specific packages[3]. They may also arise in which the ground residences, which include flora and soil kinds, vary continuously [7]. For the restricted space decision of far flung sensing pictures, every pixel of those images generally represents a huge location on the ground. For that reason, it is very feasible that a pixel is a combination of some normal floor items (endmembers) in percentage (abundance). So the way to decompose those combined pixels is a critical difficulty for excessive-accuracy classification and recognition of floor objects.

Table 1: Applications of Remote Sensing image processing

Environmental Study	**Agriculture and Forestry**	**Geology**	**Land Mapping**	**Water Resources and Oceanography**
• $Mon_{surfMin\_recl}$ • $Map\_Mon_{wat\_pop}$ • $Detec_{airpol\_eff}$ • $Deter_{natdis\_eff}$ • $Mon_{env\_eff\_man-ACT}$	• $Disc_{veg\_type}$ • $Measure_{crp\_acre\_sp}$ • $Deter_{rng\_read\_bmass}$ • $Deter_{veg\_stress}$ • $Deter_{soilCond}$ • $Deter_{soilAss}$ • $Ass_{grsFor\_fireDmg}$	• Rec_{rock_type} • Map_{geo_unit} • Rev_{geo_map} • $Delin_{un\_Ro-Soi}$ • $Map_{rec\_volSurf}$ • Map_{lndfrm} • $Deter_{reg\_str}$	• $Clas_{lnduse}$ • Cat_{lnd_capb} • Sep_{urb_rul} • Reg_{pln} • Map_{ln-wat_bond}	• $Deter_{watBond\_SurWt\_areaVol}$ • Map_{fld_fldpln} • $Deter_{arlExt-sno\_bond}$ • $Measure_{gla\_feat}$ • $Detec_{mar\_org}$ • Map_{sh_Shal} • Map_{ice_ship} • Std_{edd_wave}

$Mon_{surfMin\_recl}$- Monitoring surface mining and reclamation, $Map\_Mon_{wat\_pop}$ - Mapping and monitoring of water pollution, $Detec_{airpol\_eff}$ -Detection of air pollution and its effects , $Deter_{natdis\_eff}$ - Determination of effects of natural disasters,

Mon$_{\text{env_eff_man-ACT}}$-Monitoring environmental effects of man's activities, Disc$_{\text{veg_type}}$ - Discrimination of vegetative types, Measure$_{\text{crp_acre_sp}}$ - Measurement of crop acreage by species, Deter$_{\text{rng_read_bmass}}$ - Determination of range readiness and biomass, Deter$_{\text{veg_stress}}$ - Determination of vegetation stress, Deter$_{\text{soilCond}}$ - Determination of soil conditions, Deter$_{\text{soilAss}}$ - Determination of soil associations, Ass$_{\text{grsFor_fireDmg}}$ - Assessment of grass and forest fire damage, Rec$_{\text{rock_type}}$ - Recognition of rock types, Map$_{\text{geo_unit}}$ - Mapping of major geologic units, Rev$_{\text{geo_map}}$ - Revising geologic maps, Delin$_{\text{un_Ro-Soi}}$ - Delineation of unconsolidated rock and soils, Map$_{\text{rec_volSurf}}$ - Mapping recent volcanic surface deposit, Map$_{\text{lndfrm}}$ - Mapping landforms, Deter$_{\text{reg_str}}$ - Determination of regional structures, Clas$_{\text{lnduse}}$ - Classification land uses, Cat$_{\text{lnd_capb}}$ - Categorization of land capability, Sep$_{\text{urb_rul}}$ - Separation of urban and rural categories, Reg$_{\text{pln}}$ - Regional planning, Map$_{\text{ln-wat_bond}}$ - Mapping of land-water boundaries, Deter$_{\text{watBond_SurWt_areaVol}}$ -Determination of water boundaries and surface water area and volume, Map$_{\text{fld_fldpln}}$ - Mapping of floods and flood plains, Deter$_{\text{arlExt-sno_bond}}$ - Determination of areal extent of snow and snow boundaries, Measure$_{\text{gla_feat}}$ - Measurement of glacial features, Detec$_{\text{mar_org}}$ - Detection of living marine organisms, Map$_{\text{sh_Shal}}$ - Mapping of shoals and shallow areas, Map$_{\text{ice_ship}}$ -Mapping of ice for shipping, Std$_{\text{edd_wave}}$ - Study of eddies and waves

The major issues of interest in remote-sensing image processing but never encountered in the traditional two dimensional (2-D) image processing or three-dimensional (3-D) video processing is mixed pixels. Due to the use of spectral channels in various wavelengths, an image pixel is actually a pixel vector, of which each component is a single pixel in an image acquired by a particular spectral channel [14]. As a result, it is often the case that different substances can be diagnosed by their spectral properties in a single pixel vector. Such a substance may appear in the form of mixed by other substances in a pixel vector. In order to perform data analysis caused by mixed pixels, pure-pixel-based traditional image processing may not be directly applicable or effective.

In this paper we proposed a new approach to decompose the problem of mixed pixels. The approach is divided into two phases; phase I is the clustering of the mixed pixel dataset by using FCM-PSO algorithm so that classification will take less time and phase II we use BBO for the classification of mixed pixel in which each mixed pixel will be tagged to their actual class.

RELATED WORK

Many techniques and approaches used to solve this problem. Fuzzy techniques are used to classify sub-urban land covers from a remote sensed image. Fuzzy approaches allow more information on the relative strengths of the class membership at pixel level to be made available to end users. Thus, for instance, both data producers and users can be made aware of the potential areas vulnerable to misclassification. The information on per-pixel class membership may also be used for post-processing of image classifications [8]. Hypothesis-testing Hough transform (HTHT) is proposed which relies on the use of a soft-voting kernel and perform better in the absence of outliers as well as in the presence of outliers [9]. Linear mixing model is used to both specify the desired target and characterize the interfering background. LMM reduce the correlation between different spectral bands and it make easy to extract endmembers from abundance [10]. Target signature-constrained mixed pixel classification which imposes constraints on the direction of target signature vectors which is the combination of three aspects, one is from a sensor array processing point of view, another is from a pattern classification and third one is from a linear spectral mixture analysis point of view[11]. Gradient Descent maximum Entropy(GDME), aiming at sturdy and effective estimates from geometric factor of view and reveal that when the given facts present strong noise or while the endmember signatures are close to every other, the proposed method has the potential of offering greater accurate estimates than the famous least-squares methods (e.g., fully constrained least squares)[16]. Bayesian Self-Organizing Map (BSOM) estimates Gaussian parameters by way of minimizing the KullbackLeibler statistics metric, and finishes the unmixing with Gaussian Mixture Model (GMM). A good way to gain a high unmixing precision, we need to extend the range of Gaussian distributions, and hence endorse the 3 σ variances adjustment method to clear up this problem [17]. The Fisher discriminant null space (FDNS) searches a linear transformation of the spectra, which makes those endmember spectra to have no variability internal each endmember organization however massive differences amongst distinctive endmember agencies. Consequently, the negative effect triggered by means of endmember spectral variability on unmixing accuracy may be decreased to a massive quantity with the aid of using the transformed spectra [21]. MHNN algorithm is definitely a Hopfield-primarily based architecture which handles all of the pixels in an picture synchronously, in place of thinking about a in line with-pixel manner, because of the synchronous unmixing property of MHNN, a noise electricity percent (NEP) stopping criterion which utilizes the sign-to-noise ratio is proposed to gain premier outcomes for one-of-a-kind applications routinely[22]. Swarm primarily based mixed pixel decision set of rules is put forward primarily based on the mechanism of Biogeography primarily based optimization given that each pixel of particular land feature comes underneath the a number of DN (reflected) values or they're related on the basis of closeness and similarity between them. On the basis of DN values of bands of combined pixels, these are tagged beneath particular elegance which suggests the less deviation after including that blended pixel in it [15]. Performance of algorithm [24] is improved by hybridization of BBO with ACO. Ant Colony Optimization (ACO) used to make the clusters of mixed pixels so that the classification process will take less time [25]. Multiagent subpixel mapping framework, three sorts of retailers, specifically, characteristic detection retailers, subpixel mapping dealers and selection agents, are designed are designed to tackle the hassle of subpixel mapping within the proposed MASSM algorithm to higher reconstruct the unique types of combined pixels [34].

All the techniques till now are depending on the band value of the pixels for classification process. To get the band values for a satellite images we have to access the data of that satellite from which it is captured which is not possible to acquire it free and some time it is not available for researcher to use it. In our previous paper [40] we proposed an approach to identify and separate pure pixels from mixed pixels by using neural network and without the usage of band values of pixels. In this paper we are proposing a new algorithm which will decompose the mixed pixels to their appropriate class without using band values. This algorithm has two phases; in phase I clustering of mixed pixel will be done so that it will take less time to tagging mixed pixel to their class labels by using PFCM and in phase II the actual tagging process will take place with the help of BBO.

CLUSTERING

Clustering could be a style of unattended learning whereby objects that the same as one another are place into an equivalent cluster. It's the primary stage information of data of information acquisition regarding a bunch of objects that's getting knowledge of categories. Clustering algorithms are often loosely classified as Hard, Fuzzy, Possibilistic, and Probabilistic [5]. Fuzzy theory is the most popular technique used for clustering.

Fuzzy C-Mean (FCM)

Fuzzy c-means clustering algorithmic program (FCM) [1][28] is an efficient algorithmic prohram and is one amongst the foremost used clustering method. Fuzzy algorithms will assign data object partly to multiple clusters. The degree of membership within the fuzzy clusters depends on the closeness of the data object to the cluster centers. However once the data set includes a higher dimension, the cluster result of FCM is poor, and it's troublesome to search out the global optimum. Fuzzy c-mean technique will be outlined as; Let assume information set $\mathrm{X} = \{\mathrm{X}_1, \mathrm{X}_2, \ldots\ldots \mathrm{X}_\mathrm{n}\}$in Rd dimension space into c(1<c<n) fuzzy clusters with $\mathrm{Z} = \{\mathrm{Z}_1, \mathrm{Z}_2, \ldots\ldots \mathrm{Z}_\mathrm{c}\}$ centroids. The fuzzy cluster of objects is delineated by a fuzzy matrix μ and n rows and columns within which n is that the range of knowledge objects and c is that the range of clusters. μ_{ij}, the component within the ith row and jth column in μ, indicates the degree of association or membership perform of the ith object with the jth cluster.

The characters of μ are as follows:

$$\mu_{ij} \in [0,1] \qquad \forall\, i = 1,2 \ldots . n;\ \forall j = 1,2, \ldots\ldots . c \tag{1}$$

$$\sum_{j=1}^{c} \mu_{ij} = 1 \qquad \forall\, i = 1,2 \ldots . n \tag{2}$$

$$\sum_{i=1}^{n} \mu_{ij} < n \qquad \forall\, j = 1,2 \ldots . c \tag{3}$$

The objective function of FCM algorithm is to minimize the Eq. (4):

$$J_m = \sum_{j=1}^{c} \sum_{i=1}^{n} \mu_{ij}^{m}\ d_{ij} \tag{4}$$

$$d_{ij} = \left\| X_i - Z_j \right\| \tag{5}$$

$$Z_j = \frac{\sum_{i=1}^{n} \mu_{ij}^{m}\ x_i}{\sum_{i=1}^{n} \mu_{ij}^{m}} \tag{6}$$

The FCM algorithm is iterative and can be stated as follows [28]

Algorithm_1: FCM

Select m (m > 1); initialize the membership function values lij,

i = 1, 2, ... , n; j = 1, 2, . . . , c.

2. Compute the cluster centers zj, j = 1, 2, ... , c, according to Eq. (6).

3. Compute Euclidian distance dij, i = 1, 2, ... , n; j = 1, 2, ... , c.

4. Update the membership function lij, i = 1, 2, ... , n; j = 1, 2, ... , c according to Eq. (7).

$$\mu_{\mathrm{ij}} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{7}$$

5. If not converged, go to step 2.

There are many stopping rules that will be used. One is to terminates the formula once the relative amendment within the center of mass values becomes tiny or once the target perform, Eq. (4), cannot be decreased additional. The FCM formula is sensitive to initial values and it's possible to make up local optima.

Particle Swarm Optimization (PSO)

Particle Swarm improvement (PSO) could be a population-based improvement tool, that may well been forced and appied simply to unravel numerous performance improvement issued, that may be remodeled to perform improvement problems. Particle swarm improvement (PSO) could be a population-based random improvement technique impressed by bird flocking and fish schooling [6] and relies on iterations/generations. The algorithmic flow in PSO starts with a population of particles whose positions represent the potential solutions for the studied downside, and velocities square measure every which way initialized within the search area. In every iteration, the look for best position is performed by changes the particle velocities and positions. Conjointly in every iteration, the fitness value of every particle's position is set employing fitness function. The speed of every particle is updated by using two best positions, personal best position and global best position. The personal best position, p best, is that the best position the particle has visited and gbest is that the best position the swarm the swarm has visited since the primary time step. A particle's velocity and position are updated as follows.

$$\mathrm{V}(t+1) = w.\mathrm{V}(t) + c_1 r_1\big(\mathrm{pbest}(t) - \mathrm{X}(t)\big) + c_2 r_2\big(\mathrm{gbest}(t) - \mathrm{X}(t)\big); \qquad k = 1,2,\ldots \mathrm{P} \tag{8}$$

$$\mathrm{X}(t+1) = \mathrm{X}(t) + \mathrm{V}(t+1) \tag{9}$$

Where X and V are position and velocity of particle severally. w is inertia weight, c1 and c2 are positive constants, known as acceleration coefficients that manage the influence of pbest and gbest on the search method, P is that the variety of particles within the swarm, r1 and r2 are random values in vary [0, 1] .

Hybridization of PSO and FCM

The way of FCM method is to apply the gradient descent technique to discover ideal solution , so there is a local optimization issue. Furthermore, the calculation union velocity is incredibly affected by the initial value, particularly on account of expansive number of groups. PSO is a viable worldwide enhancement approach. This paper applies fuzzy c-mean clustering method based on particle swarm optimization in satellite image processing for grouping mixed pixels and the hybridization of both can improve bunching results.In this paper first Fuzzy C mean is appy to seclect the centroid of the clusters and the PSO is used to select the population that belongs to that cluster. Both algorithms perform their function individually as well as communicate with each other for mutual benefits and complementarities to enhance the quality of clustering.

Algorithm: FCM -PSO

1. Initialize the parameters of FPSO and FCM including population size P, c_1, c_2, w and m.

2. Create a swarm with P particles (X, pbest, gbest and V are n×c matrices)

3. Initialize X,V, pbest for each particle and gbest for the swarm

4. FPSO algorithm:

// Where c-mean partitions set of n objects o={o1,o2,…on} in R_d dimension space into c(1<c<n) fuzzy clusters with Z= {z1,z2,….zc} cluster centers or centroids. The fuzzy clustering is define in matrix μ having n rows and c columns in which n represent the number of data objects and c is the count of clusters. μ_{ij} the element in the i^{th} row and j^{th} column in μ, indicates the degree of association or membership function of the i^{th} object and j^{th} cluster and m (m > 1) is a scalar termed the weighting exponent and controls the fuzziness of the resulting clusters.//

4.1 Calculate the cluster centers for each particle using

$$Z_j = \frac{\sum_{i=1}^{n} \mu_{ij}^{m} o_i}{\sum_{i=1}^{n} \mu_{ij}^{m}}$$

4.2 Calculate the fitness value of each particle using

// where K is a constant and J_m is the objective function of FCM algorithm

$$f(x) = \frac{K}{J_m}$$

4.3 Compute *pbest* for each particle.

4.4 Compute *gbest* for the swarm

4.5 Update the velocity matrix for each particle

4.6 Update the position matrix for each particle

4.7 If FPSO termination criteria not reached go to step 4

5. FCM algorithm

5.1 Calculate cluster center for each particle as in step 4.1

5.2 Compute Euclidian Distance d_{ij}. *i=1,2,…n and j= 1,2,..c* for each particle and using $d_{ij} = \|o_i - z_j\|$

5.3 update membership function μ_{ij}. *i=1,2,…n and j= 1,2,..c* for each particle using $\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}}$

5.4 Calculate *pbest* for each particle.

5.5 Calculate *gbest* for the swarm

5.6 If FCM termination criteria not reached go to step 5

6. If FCM-FPSO termination criteria not reached go to step 4

As same as other evolutionary algorithm this hybrid algorithm also required fitness function to generalized the solution so, E is the fitness function used in this paper and it is defined as:

PSO fitness function:

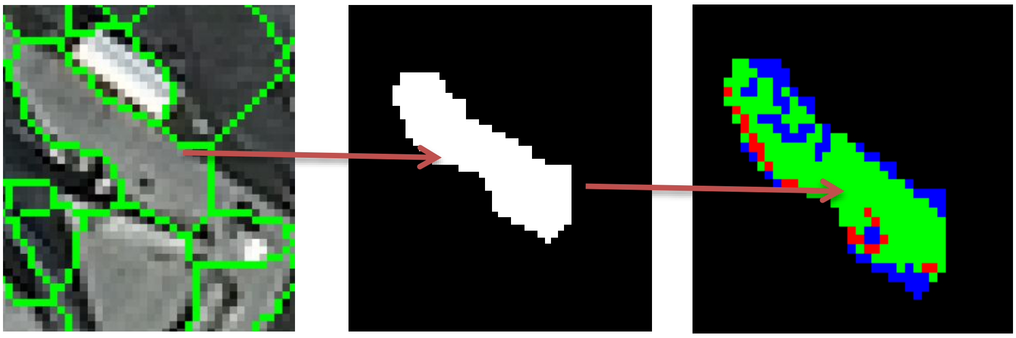
$$E = \sum_{n=1}^{n=z} \sqrt{(C_1 - P_{rx})^2 + (C_2 - P_{gx})^2 + (C_3 - P_{bx})^2} \qquad (10)$$

$$Fitvalue = 1 - E/(Z) \qquad (11)$$

- Where C_1 , C_2 , C_3 are the chosen RGB centroid values for current cluster
- P_{rx}, P_{gx} , P_{bx} are the RGB components for current cluster which is going to be sub clustered
- z is the number of pixels to get clustered
- Z is the max pixels present in biggest cluster

Figure 1 shows the ouput clustered image of mixed superpixel by using PFCM. Different Clusters are differiated by using different colours.

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 8 (2018) pp. 5736-5744



(a) (b) (c)

Figure 1. (a) super pixel images, (b) super pixel sample, (c) clustered super pixel

LASSIFICATION

In this pahse of expirement the mixed pixels in an image is classified to their respective classes. For this in this paper BBO is used with NN.

Biogeography-Based Optimization

Biogeography based Optimization (BBO) is a populace primarily based evolutionary algorithm (EA) influenced by the migration mechanisms of ecosystems [19]. It's miles based on the arithmetic of biogeography. In BBO, trouble solutions are represented as islands, and the sharing of functions among answers is represented as emigration and immigration. One function of BBO is that the authentic population is not discarded after each era. It's far rather changed by using migration. also for every generation, BBO makes use of the fitness of each way to decide its emigration and immigration price. Different distinguishing function of BBO is that after updating the populace, BBO considers the fitness of the immigrating and emigrating islands via immigration and emigration curves. In BBO, each person solution is taken into consideration as a habitat with a habitat suitability index (HSI), to degree the suitability of man or woman. Also, an SIV (suitability index variable) which characterizes the habitability of an island is used. An excellent answer is similar to an island with a high HSI, and a bad answer suggests an island with a low HSI. Excessive HSI solutions tend to proportion their functions with low HSI answers. Low HSI solutions are given lots of new capabilities from high HSI solutions. In BBO, every character has its own immigration price λ and emigration rate μ. A better solution has better emigration rate μ and lower immigration rate λ.

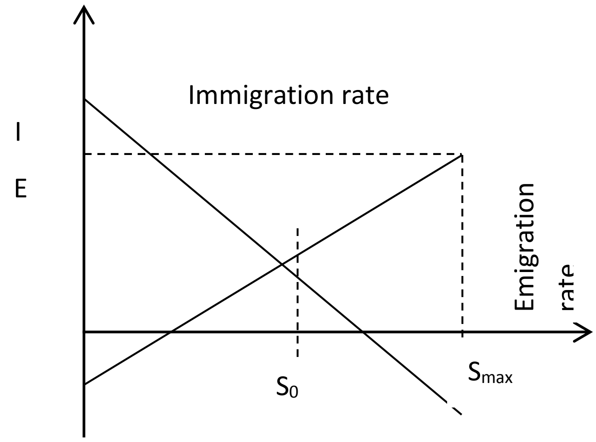


Figure 2. Relationship between species count, immigration rate and emigration rate. Figure from [34].

Now, assume that at time t, the receiver island has S species with probability (t), and λs is the immigration rate and μs is the emigration rate at the current of S species on that island. So the changes from Ps(t) to Ps(t+Δt) can be defined as [19]:

$$Ps(t+\Delta t) = Ps(t)(1-\lambda s\Delta t-\mu s\Delta t) + Ps-1(t)\lambda s-1\Delta t+Ps+1(t)\mu s+1\Delta t \quad (13)$$

This equation is true only when the following conditions will be true and have S species at (t+Δt) time:

i. There were S species at t time , and no immigration or emigration occurred between t and (t + Δt);
ii. There were (S-1) species at time t , and one species immigrated;
iii. There were (S+1) species at time t, and one species emigrated.

BBO fitness function:

$$F = \frac{\sum_{i=1}^{i=\eta}(\alpha_i \,.\, w_1 + \beta_i \,.\, w_2 + \gamma_i \,.\, w_3) - C_i}{\eta} \quad (14)$$

Where η is the number of samples to be used to train the weights of BBO

$\alpha_i, \beta_i, \gamma_i$ are the RGB components of i^{th} sample

w_1, w_2, w_3 are the respective weights of BBO to get the classification optimization

C_i is the actual category of i^{th} sample.

ALGORITHMIC PROCESS

The stages followed to in this paper to classifeied the mixed pixels to their appropriate classes are given in figure 3. The approach used in this thesis is divide into two section: first the dataset used in this research is generated as preexisting dataset is not used because it is observed from the literature that in previously used techniques for mixed pixel classification the dataset used is Band values or DN values of the pixels captured by satellites. But, if the band values are not available, then, how to implemented the algorithms? Also by using existing dataset the algorithm works on images of same size and same resolution. For this new approach has been developed for generating dataset without having satellites DN values against every pixel of an image. Second part is the classification part.

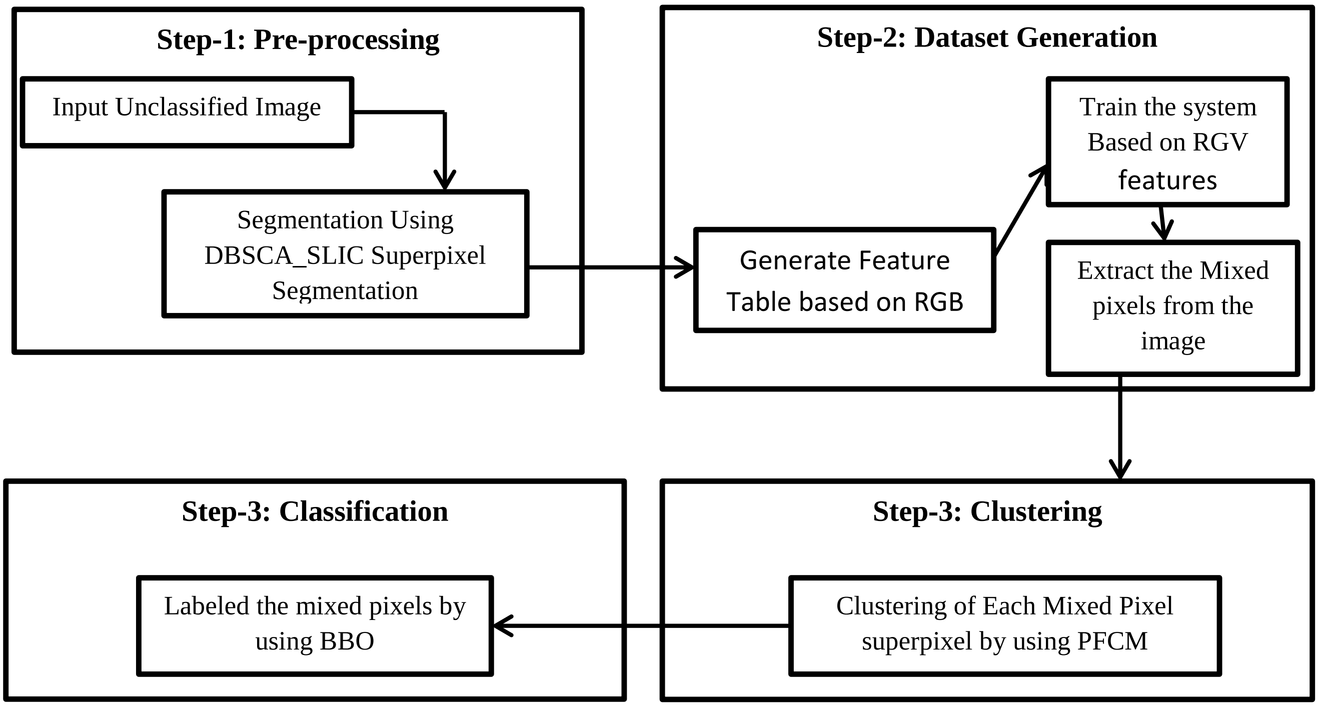


Figure 3. Flow chart of the proposed methodolog

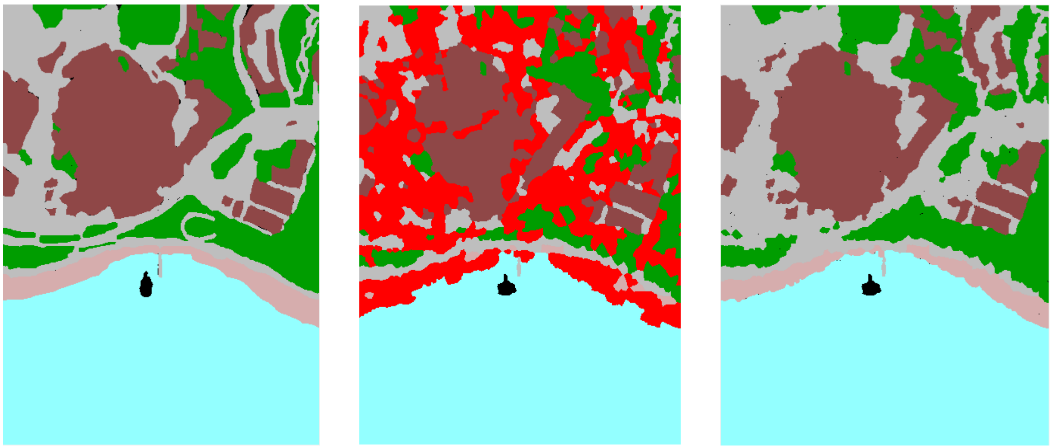
The first step of this methodology is Super pixel segmentation performed on input images. Superpixel is a group of connected pixels with similar colors or gray levels. Superpixel segmentation is dividing an image into hundreds of non-overlapping superpixels. Instead of working with just pixels. In this approach for super pixel segmentation DBSCAN SLIC algorithm is used. The super pixel image results in a grid image having different clusters but there is an issue with it. Superpixel image also have minor clusters with in a parent cluster. To process such child clusters are time consuming. For this we proposed a new algorithm with merge the child super cluster in its parent super cluster if its neighbors are having same intensity values. After this merged super pixel image the RGV fractures are extracted from the super pixels and neural network is used to train the system on this fractures to classify the image in mixed pixels and pure pixels we used Random forest classifier. To choose the classifier analytic study on different classifier has been perform and from various performance factors Random forest gives the higher accuracy. At the end the dataset of mixed pixel and pure pixel is generated. This dataset generation technique's performance is also compare with existing mixed pixel extraction techniques like PPI, N-Finder, IEA, VCA, etc. against RMSE and computation time and it perform better. After getting the dataset of mixed pixel the clustering process is started to for sub clusters of super clusters. The benefit of this clustering is that there is no requirement to classify each and every pixel of superpixel. Here only $1/4^{th}$ pixels of sub cluster of mixed pixel superpixel have to be verified and assigned to the particular class then the rest pixels that belongs to that sub cluster of super pixel will be by default belongs to that class. It helps to reduce the processing time of classification. In this research hybridization of PSO based fuzzy c-mean algorithm is used for this clustering. After this step of clustering for mixed superpixel sub cluster are classified and labeled to their respective class or spectral features. Classification of mixed pixel is done by using combination of neural network and Biogeography Based Optimization (BBO). Here in this research work we proposed new method

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 8 (2018) pp. 5736-5744

of weight assignment of based on BBO to neural network which enhance and optimize the neural network process to classify the mixed pixel to its appropriate class.

RESULTS

By implementiong the above mention methodology the following results have been achived. Figure 4 shows the final classified image.



a b c

Figure 4 (a) original images (b) Image with mixed pixels, (c) Final classified images

To measure the performance of proposed methodlogy various performance evlaution parameters are claulated. Figure 5 gives the values of performance measuring parameters. Three images are shown from complete data set and the values of parameters corresponding to the respective class are given in this able.

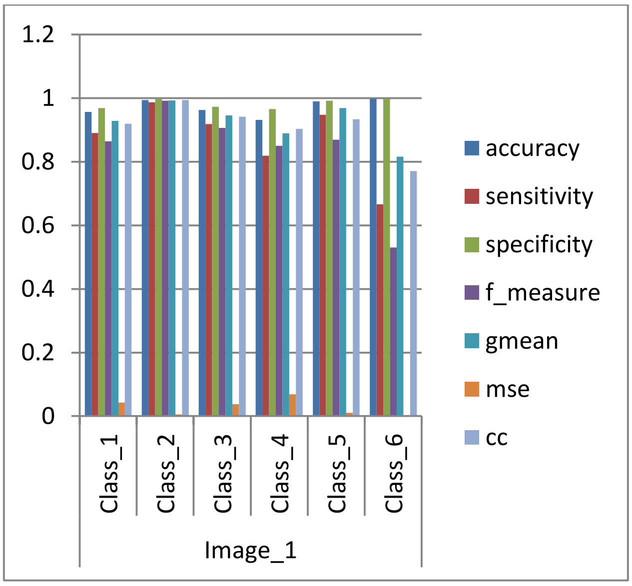


Figure 5: Performance evaluation

The proposed methodology works better than the other existing te chniques. To compare the results of this techniques with other the test-case accuracy parameter is used and it shows that this technique performance is much bettere then the already existing ones.

Table 2: Comparison of Proposed Algorithm with previous Methods

Sr. No	Algorithm	Test-Case Accuracy
1	Fuzzy C-mean	68.9
2	ANN	74.1
3	RBFNN	77.2
4	RF	76.1
5	Random Forest with RGB features	44
6	CNN with RGB features	44.5
7	RBF_SVM	84.07
8	Knowledge Based Method	94.2
9	Proposed Method	96.1

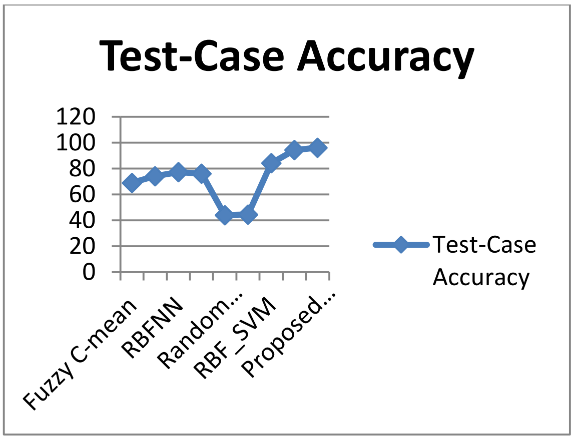


Figure 6: Test- Case Accuracy of the different algorithms.

CONCLUSION AND FUTURE SCOPE

Most of the time spatial resolutions of remote stellate are very coarse and inappropriate for the particular application to perform optimal mapping. The data gathered regarding Land cover classes in such scenario should be done with more care. Because, the errors and uncertainties in this data if goes unrecognized it will affect all classification process. To make classification procees more efficient by decomposing mixed pixels to their repective classes we developed a probabilistic methodology, considering the fact that hybridization of optimization and soft computing methods can efficiently cope with the existence of mixed pixels in remote sensing images. Its evident that the proposed approach for mixed pixel classification work better and efficient than the other techniques. Its accuracy is high and RMSE is low as compare to other techniques, which 96.1% and 0.032607 respectively.

REFERENCES

[1] Bezdek, James Christian. "Fuzzy mathematics in pattern classification." (1973).

[2] Townshend, John RG, "*Terrain analysis and remote sensing*", George Allen and Unwin, (1981)

[3] Campbell, J.B., "Introduction into Remote Sensing", The Guildford Press, New York, (1987)

[4] Lillesand, Thomas M., and Ralph W. Kiefer. "Remote sensing and photo interpretation." John Wiley and Sons: New York, p. 750 (1994)

[5] Hathaway, R. J., & Bezdek, J. C., "Optimization of clustering criteria by reformulation", IEEE transactions on Fuzzy Systems, vol. 3, No. 2, pp. 241-245 (1995).

[6] Kennedy, J., & Eberhart, R. Particle swarm optimization. In Proceedings of the IEEE international conference on neural networks , pp. 1942–1948 (1995)

[7] Foody, G. M., "Relating the land-cover composition of mixed pixels to artificial neural network classification output", Photogrammetric Engineering and Remote Sensing, vol.62, No. 5, pp. 491-498 (1996)

[8] J. Zhang & G. M. Foody, "A fuzzy classification of sub-urban land cover from remotely sensed imagery", International Journal of Remote Sensing, vol. 19, No. 14, pp. 2721-2738, (1998)

[9] P. Bosdogianni, M. Petrou, J. Kittler, "Classification of sets of mixed pixels with the hypothesis-testing Hough transform", IEEE Proc.-Vis. Image Signal Process., Vol. 145,No. 1, pp. (1998)

[10] Dimitris Manolakis, Christina Siracusa, and Gary Shaw, "Hyperspectral Subpixel Target Detection Using the Linear Mixing Model", IEEE Transactions On Geoscience And Remote Sensing, Vol. 39, No. 7, pp. 1392-1409 (2001).

[11] Chein-I Chang, "Target Signature-Constrained Mixed Pixel Classification for Hyperspectral Imagery", IEEE Transactions On Geoscience And Remote Sensing, vol. 40, No. 5, pp. 1065-1081 (2002)

[12] Naoko Kosaka, Kuniaki Uto, Yukio Kosugi, "ICA-Aided Mixed-Pixel Analysis of Hyperspectral Data in Agricultural Land", IEEE Geoscience and Remote Sensing Letters, vol. 2, No. 2, pp. 220-224 (2005)

[13] Chang, C. I., & Ji, B., " Fisher's linear spectral mixture analysis", IEEE transactions on geoscience and remote sensing, vol. 44, No. 8, pp. 2292-2304 (2006)

[14] Chein-I Chang, "Fisher's Linear Spectral Mixture Analysis", IEEE Transactions On Geoscience And Remote Sensing, VOL. 44, NO. 8, pp.2292-2304, (2006)

[15] King, R. L., & Younan, N. H., "Pixel unmixing via information of neighboring pixels", GIScience & Remote Sensing, vol. 43, No. 4, pp. 310-322 (2006)

[16] Lidan Miao, Hairong Qi and Harold Szu, "A Maximum Entropy Approach to Unsupervised Mixed-Pixel Decomposition", IEEE Transactions On Image Processing, vol. 16, No. 4, pp. 1008-1021 (2007)

[17] Liu, Lifan, et al. "Decomposition of mixed pixels using Bayesian Self-Organizing Map (BSOM) neural networks." 2007 IEEE International Geoscience and Remote Sensing Symposium. IEEE, pp.2014-2017 (2007)

[18] Godbaz, J. P., Cree, M. J., & Dorrington, A. A. , " Mixed pixel return separation for a full-field ranger", In 2008 23rd International Conference Image and Vision Computing New Zealand ,IEEE, pp.1-6 (2008)

[19] Simon, D. "Biogeography-based Optimization", in IEEE Transactions on Evolutionary Computation, IEEE Computer Society Press. , vol. 12, No.6pp. 702-713 (2008)

[20] Tao, X., Wang, B., & Zhang, L., "Orthogonal bases approach for the decomposition of mixed pixels in hyperspectral imagery", IEEE Geoscience and Remote Sensing Letters, vol. 6, No.2, pp. 219-223 (2009)

[21] Jin, J., Wang, B., & Zhang, L. , "A novel approach based on fisher discriminant null space for decomposition of mixed pixels in hyperspectral imagery", IEEE Geoscience and Remote Sensing Letters, vol.7, No. 4, pp. 699-703 (2010)

[22] Mei, S., He, M., Wang, Z., & Feng, D., “Mixture analysis by multichannel Hopfield neural network”, IEEE Geoscience and Remote Sensing Letters, vol. 7, No. 3, pp. 455-459(2010)

[23] Luciani, P., & Chen, D., “ The impact of image and class structure upon sub-pixel mapping accuracy using the pixel-swapping algorithm”, Annals of GIS, vol. 17, No. 1, pp. 31-42 (2011)

[24] Panchal, V. K., and Nitish Gupta. "Swarm intelligence for mixed pixel resolution." IEEE Geo Sciences and Remote Sensing Symposium (IGRASS), pp-2801-2804. (2011)

[25] Sinha, Suruchi, et al. "Resolving mixed pixels by hybridization of biogeography based optimization and ant colony optimization." 2012 IEEE Congress on Evolutionary Computation. IEEE, pp. 1-6 (2012)

[26] Su, Y. F., Foody, G. M., Muad, A. M., & Cheng, K. S., “Combining Hopfield neural network and contouring methods to enhance super-resolution mapping”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 5, No. 5, pp. 1403-1417 (2012)

[27] Sriwilai, S., Kasetkasem, T., Chanwimaluang, T., Srinark, T., & Isshiki, T., “A super-resolution mapping algorithm based on the level set method”, In Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2013 10th International Conference, pp. 1-6 (2013)

[28] Alpaydin, Ethem. Introduction to machine learning. MIT press, (2014)

[29] Cerra, D., Müller, R., & Reinartz, P., “Noise reduction in hyperspectral images through spectral unmixing”, IEEE Geoscience and Remote Sensing Letters, vol. 11, No. 1, pp. 109-11 (2014)

[30] Chen, Y., Ge, Y., Wang, Q., & Jiang, Y., “A subpixel mapping algorithm combining pixel-level and subpixel-level spatial dependences with binary integer programming”, Remote sensing letters, vol. 5, No. 10, pp. 902-911 (2014)

[31] Cubero-Castan, M., Chanussot, J., Achard, V., Briottet, X., & Shimoni, M., “A physics-based unmixing method to estimate subpixel temperatures on mixed pixels”, IEEE Transactions on Geoscience and Remote Sensing, vol. 53, No. 4, pp. 1894-1906 (2014)

[32] Khodadadzadeh, M., Li, J., Plaza, A., Ghassemian, H., Bioucas-Dias, J. M., & Li, X., “Spectral–spatial classification of hyperspectral data using local and global probabilities for mixed pixel characterization”, IEEE Transactions on Geoscience and Remote Sensing, vol.52, No, 10,pp- 6298-6314(2014)

[33] Iordache, M. D., Tits, L., Bioucas-Dias, J. M., Plaza, A., & Somers, B., “A dynamic unmixing framework for plant production system monitoring”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 7, No. 6, pp. 2016-2034 (2014)

[34] Xu, X., Zhong, Y., & Zhang, L., “Adaptive subpixel mapping based on a multiagent system for remote-sensing imagery”,IEEE Transactions on Geoscience and Remote Sensing, vol. 52, No. 2, pp. 787-804 (2014)

[35] Zhang, L., Zhang, L., Tao, D., Huang, X., & Du, B., “Hyperspectral remote sensing image subpixel target detection based on supervised metric learning”, IEEE Transactions on Geoscience and Remote Sensing, vol. 52, No. 8, pp. 4955-4965 (2014)

[36] Chen, Y., Ge, Y., Heuvelink, G. B., Hu, J., & Jiang, Y., “Hybrid constraints of pure and mixed pixels for soft-then-hard super-resolution mapping with multiple shifted images”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, No. 5, pp. 2040-2052 (2015)

[37] Guerra, R., Santos, L., López, S., & Sarmiento, R., “A new fast algorithm for linearly unmixing hyperspectral images”, IEEE Transactions on Geoscience and Remote Sensing, vol. 53, No. 12, pp. 6752-6765 (2015)

[38] Yuan, Y., Fu, M., & Lu, X., “Substance dependence constrained sparse NMF for hyperspectral unmixing”, IEEE Transactions on Geoscience and Remote Sensing, vol. 53, No. 6, pp. 2975-2986 (2015)

[39] Zhang, T., Jiang, L., Chai, L., Zhao, T., & Wang, Q., “Estimating Mixed-Pixel Component Soil Moisture Contents Using Biangular Observations From the HiWATER Airborne Passive Microwave Data. IEEE Geoscience and Remote Sensing Letters, vol. 12, No. 5, pp. 1146-1150 (2015)

[40] Kaur, Sumit, and R. K. Bansal, "Novel Approach for Mixed Pixel Extraction from Remote Sensing Images." International Journal of Applied Engineering Research 12(22), 12860-12871(2017).