PROPOSED MODEL TO MEASURE THE EFFECT OF DISCONTINUITY ADAPTIVE MRF MODELS IN FUZZY BASED CLASIIFIER ON SATELLITE IMAGES

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Abstract

Presently wide ranges of remotely sensed data are available from earth observation satellites. This data are analyzed to prepare land use/ land cover maps using different remote sensing techniques. Image classification is one way to produce these land use/ land cover maps. Due to continuous nature of real world phenomena, the image classification to map land cover classes is a challenge. Presence of mixed pixels decreases the efficiency of image classification. Fuzzy classification technique such as Fuzzy c-Means (FCM) can be used to handle mixed pixels. Although FCM has the advantage of classifying mixed pixels by assigning membership value, it does not incorporate spatial contextual information of the pixels into its classifying algorithm. Use of context eliminates the problem of isolated pixels and improves the classification accuracy. In this research work a contextual FCM classifier has to be developed by using MRF models. Smoothness prior and four discontinuity adaptive prior have been used to incorporate contextual information with FCM. The developed discontinuity adaptive contextual FCM classifier would be tested both on coarse and fine resolution dataset i.e. AWFIS and LISS-III with spatial resolution 60 m and 20m respectively. It is expected that the discontinuity adaptive prior models, improves the overall classification accuracy by preserving the edges at boundaries and the classified output is consistent with spectrally and spatially.

Key words: Fuzzy c-means clustering, contextual, Markov Random field, Discontinuity Adaptive, Edge preservation

Introduction

The number of remote sensing satellites with coarse to fine resolution launched worldwide are increasing. These satellites provide a large amount of remote sensing images of the earth resources. Such satellite images contain wealth of information which play a significant role in the development and planning of natural resources.

Satellite images are further analyzed to prepare land / use land cover maps using digital image processing techniques in a fast and economic way. These land use/ land cover maps are the important input for any kind of development and conservation projects. Image classification is important to produce these land use land cover maps. In image classification, pixels representing similar objects are grouped together to form land cover classes or clusters.

The most commonly used classifiers are the hard classifiers. They assume that a pixel takes either 1 or 0 memberships to a single class and the pixel is considered as a pure pixel. The pixels have membership value equal to 0 for the classes to which they do not belong and membership value equal to 1 for the class to which they belong. For actual data, however, a single pixel can contain more than one class, such as a combination of, forest, water, bare soil and grass. This happens because real world phenomena change gradually from one class to another as well as due to compatibility of spatial resolution with class size forms mixed pixels. Therefore at the boundaries of different classes uncertainty increases and fuzziness or vagueness occurs.

To overcome the problem of multiple classes at the boundaries in 1965, L.A Zadeh introduced fuzzy set theory which is based upon uncertainty and vagueness [1]. Fuzzy sets can have the membership values between 0 and 1 also. The degree of the membership value can be assigned for a pixel which handles the problem of having multiple classes in a pixel. This means that a pixel is assigned to more than one cluster. Fuzzy c-means clustering (FCM) [2] is one of the popular fuzzy based soft classification technique which takes care of uncertainty and vagueness in class definition.

Fuzzy c-Means clustering (FCM) introduced by Bezdek [2] is a well-known unsupervised iterative algorithm to calculate the fuzzy membership grades. FCM finds the cluster center based on the minimization of an objective function. The objective function of FCM clusters the patterns in a similar group which have highest similarity. Standard FCM does not incorporate spatial contextual information of the pixels into its classifying algorithm; it considers only the spectral information of the pixels.

To incorporate spatial contextual information Markov Random Field (MRF) is being widely used [3],[4],[5].MRF theory is able to model context dependent entities such as pixels or correlated features in a convenient and consistent way [5].Spatial context implies the presence of correlation of class labels within neighbouring pixels [4]. The actual geographical phenomenon lies in context to others. For example vegetation has a high probability to have the same vegetation pixels as its neighbours. So the isolated pixels exist rarely. Use of context eliminates the problem of isolated pixels [6]. In this research work, MRF has been used to develop the contextual based supervised FCM classifier

To model the context it is important to select the MRF models carefully for accurate results. The MRF models also called as MRF priors and regularizers. The various MRF models are standard regularization model, weak string and membrane model, line process model, and Discontinuity adaptive (DA) MRF models.
In this research work standard regularization model (smoothness prior) and discontinuity adaptive (DA) models (edge preserving priors) have been studied for smoothing effect as well as edge preserving effect in image.

Problem statement

MRF uses smoothness prior models and calculates prior energy using prior probabilities to model the smoothness in the images [6]. This applies smooth contextual concept, assumes uniform smoothness everywhere. If discontinuities are overlooked (e.g. at boundaries), however MRF leads to over-smoothing, loss of information and hence to less accurate results [5],[7]. Smoothness priors can be used which can preserve the edges as mentioned by Li [5].Discontinuity adaptive (DA) models [7] or adaptive neighbourhoods [8] can be used to overcome the problems of discontinuity. Hence this research work proposes to study the effect of various discontinuity adaptive MRF models in fuzzy c-means classifier.

Research objectives

The main objective of this study is to incorporate spatial contextual information in FCM using discontinuity adaptive MRF models. The specific objectives are as follows;

1. To incorporate spatial contextual information in FCM using DA MRF models.
2. Study of four DA MRF models for FCM.
3. To develop a FCM classifier incorporating spatial contextual information using DA MRF that preserves edges.
4. To evaluate the performance of the FCM-DA MRF in case of untrained classes

Research questions

In order to meet the solutions of the above mentioned objective the following questions need to be answered.

1. How can spatial contextual information be incorporated with FCM classification when DA MRF models are to be used?
2. How should the FCM objective function be formulated to allow incorporation of context using DA- MRF models?
3. Which is a suitable DA MRF model for FCM?
4. What is the accuracy of the FCM adjusted with DA MRF as compared to FCM?
5. How much accuracy does FCM-DA MRF improve as compared to FCM with smoothness prior MRF?
6. How does FCM-DA MRF perform in case of untrained classes?

Research set up

To obtain the research objective and to answer the research questions, the following methodology showed in figure 1 has been adopted. The complete methodology for this study can be divided into three stages.

1. FCM-MRF model: Spatial contextual information has been incorporated with FCM using smoothness prior (FCM-S) and using discontinuity adaptive priors (FCM-DA).
2. Classification: Classification of coarse and medium resolution images have been performed by FCM, FCM-S and FCM-DA separately.
3. Accuracy measure: Accuracy assessment of classified fraction images using Fuzzy Error Matrix (FERM) [9] , Sub-Pixel Confusion Uncertainty Matrix [10].

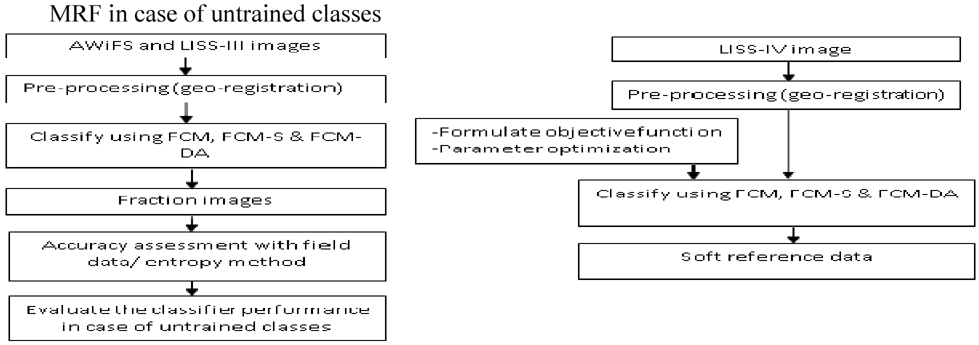

Figure 1: General methodology adopted for this study

Fuzzy c-Means clustering

Wang [11] used supervised FCM classification to classify Landsat MSS and TM data. FCM classifier was able to identify the land cover classes from the mixed pixels. The overall classification accuracy of 5.11% had been improved as compare to the maximum likelihood classifier. Zhang and Foody [12] tested the FCM on SPOT HRV and Landsat TM. It was observed that in case of sub-urban land cover mapping fuzzy classification provided more appropriate classification results. The 20% improvement in accuracy had been observed in comparison to the hard classifier.

Okeke and Karnieli [13] applied FCM classification on aerial photograph to find out quantitative changes in trees and other vegetation types. Combined supervised and unsupervised FCM algorithm was used for the classification of aerial photographs for change analysis. In this work for output evaluation Fuzzy Error Matrix (FERM) was used whereas ground reference data were not available and the fuzzy overall accuracy for all the datasets were more than 85%.

Lucas *et al*. [15] used FCM and linear mixture model on the airborne imaging spectrometer (CASI) images to map the habitat of costal dune ecosystem. Spectral unmixing of CASI image was done by linear mixture model and fuzzy membership function. Both the classifier techniques were able to map the sand and vegetation successfully at the sub-pixel level. It was concluded form the study that FCM and linear mixture model could be useful to map the land cover class at sub-pixel level.

Foody [16] has applied FCM and fuzzy neuron network (ANN) on airborne thematic mapper (ATM) data to classify land cover classes. In FCM classification it was found that with m=2.0 (fuzzy weight parameter) provided high accuracy for maximum cases. Finally in this work it was concluded that in comparison to hard classification approach fuzzy classification gives higher accuracy for land cover classification.

In another work Zhang and Foody [17] applied FCM and ANN technique to classify sub-urban land cover from Landsat TM data. The improvement in classification accuracy of 5.0 % to 6.6% had been noticed for the fuzzy classifier in comparison to partially-fuzzy approach.

Bastin [19] showed that FCM gave better sub-pixel land-cover classification on aggregated TM image. In this work comparative study was conducted among FCM, linear mixture modelling and maximum likelihood classifier while classifying aggregated Landsat TM image.

Ibrahim *et al*. [20] showed the need of mixed pixel image classification to generate more accurate land cover classes. In this work the maximum likelihood classifier (MLC), Fuzzy c-means classifier (FCM) and possibilistic c-means classifier (PCM) had been studied in presence of uncertainties and found that PCM gave more accurate results followed by FCM. The accuracy obtained from the error matrix, were 66.8%, 69.2%, 70.0% for MLC, FCM, PCM respectively.

Markov Random Field

Geman and Gema [3] did maximum a priori (MAP) estimation as statistical criterion using simulated annealing and Gibbs Sampler for MRF based image restorations. It was found improved restorations at low signal-to-noise ratio. This paper explains the equivalence between Gibbs distribution and Markov random field (MRF). The restoration was performed using the simulated annealing theorem which convergence to the global maxima of the posterior distribution. Similar simulated annealing algorithm was used in this M.Sc thesis to find out the global posterior energy without sticking in a local minimum.

Solberg *et al* [4] used MRF to include context for multisource satellite images. It was found that MRF can model spatial class dependencies as well as temporal class dependencies. MRF model achieved 2% higher classification accuracy when same set of image used for the two different models. Finally it was conclude that MRF model provide better results for classification of multisource satellite images.

Pham [21] included spatial constraints using MRF on the membership function of FCM for image segmentation and it was named as Robust Fuzzy C-means or RFCM algorithm. The value of smoothness controller β was obtained by the penalty function or objective function. In this work the new formulation of FCM was applied on Magnetic Resonance Images (MRI) of brain and it was found that RFCM to be more robust to noise than FCM classification. The comparative results calculated by misclassified rate (MCR) was 14.14% for FCM and for RFCM it was 0.52%.

Melgani and Serpico [22] used MRF to integrate contextual and spatio- temporal information for the classification of Landsat TM and ERS-1 SAR images. In this work it was proposed a "mutual" approach for image classification. In this study it was found that proposed "mutual"method shows improvement of 1% to 3% in classification accuracy as compare to reference MRF-based classifier.

Tso and Olsen [23] have used contextual and multiscale fuzzy line process for classification of IKONOS image. MRF was used for contextual information, wavelet and fuzzy fusion process to extract line features. The accuracy was improved to 13%, while using MRF based contextual and edge information image classification.

Kasetkasem *et al* [24] used MRF for super-resolution land cover mapping. In this work the proposed MRF model based approach was applied on IKONOS MSS and Landsat ETM+ images. The results showed a significant improvement in accuracy of land cover maps over that obtained from Land cover mapping at sub pixel scales using Linear Optimization approach given by Verhoeye and wulf (2002).

Moser and Serpico [25] proposed contextual support vector machines (SVM) classifier based on MRF model. To minimize the execution time and to automatically tune its input parameters hierarchical clustering and parameter optimization algorithm was also integrated with SVM. The developed method was applied on SAR and multispectral high resolution images. The overall accuracy was 0.9392 and 0.9898 for traditional SVM and proposed MRF based SVM respectively.

More details on MRF based images analysis is available in Li [5]. This book provides the reference to theories, methodologies and recent developments in computer vision problems based on MRF. The various problems were discussed in low and high level vision problem within the MAP-MRF framework.

Discontinuity Adaptive MRF models and over smoothing

Li [7],[26] introduced Discontinuity Adaptive (DA) MRF models to avoid over smoothing. The major differences among different discontinuity adaptive MRF models lies how they interact with their neighboring points and control the smoothing strength. The DA models works in the principle that whenever a discontinuity occurs it minimize the smoothing strength accordingly.

Smits and Dellepiane [27] used discontinuity adaptive MRF model combined with gamma distribution for segmentation of synthetic aperture radar (SAR) images. The developed method was able to preserve the fine structure and borders of the images.

In another work by Smits and Dellepiane [28] used MRF combining with Adaptive Neighbourhoods segmentation of synthetic aperture radar (SAR) images. It was found that MRF segmentation approach with adaptive neighbourhood can preserve the small features in better way.

Homen *et al* [29] used MRF for super resolution image reconstruction using Iterated conditional modes (ICM) algorithm to find maximum a posterior (MAP) solution. Discontinuity adaptive framework was used to avoid over smoothness of MAP-MRF formulations for sixteen low-resolution (LR) images.

Kang and Roh [30] presented a new method to increase the performance of edge-preserving image smoothing of MRF function by the parameter tuning. The method was based on an automatic control of smoothing- strength in discontinuity adaptive MRF function from discontinuities of image intensity. An algorithm was proposed which used parameter modification to increase the piecewise smoothness of images in a discontinuity adaptive (DA) MRF modelling. The proposed method was well preserved the object boundaries in comparison to conventional DA smoothing.

Debayle and pinoli [31] used adaptive neighbourhood image processing on a real human retina image. The used adaptive neighbourhood approach was context-dependent analysis which considers the radiometric as well as geometric properties of the image.

Accuracy measure and validation

Accuracy assessment and validation of soft classification output is still a research area. In case of hard classification output error matrix and kappa coefficient is being widely used for accuracy measure but there are no such standard methods for soft classifiers output. Some researchers have hardened the soft classifiers output, but doing so it leads to loss of information [9].

To carry out the accuracy measure of the soft classified output, a modified error matrix i.e. FERM (Fuzzy Error Matrix) has been proposed by the Binaghi *et al.*[9] and SCM (Sub-pixel confusion –uncertainty matrix) has been proposed by Silvan and Wang [10]. This fuzzy error matrix is used to derive the accuracy of soft classifier when the output is fraction images. FERM is used the same as the traditional error matrix but the main difference is that FERM uses fractional images to measure the accuracy and the values in FERM are real number (integers in conventional error matrix). The overlap between classified and reference datasets is calculated by using single operators like Min, Least and Prod or composite operators like MIN-MIN and MIN-LEAST and MIN-PROD [10], [32].

Dehghan and Ghassemian [33] had given entropy measure to assess the accuracy of the classified output by measuring the uncertainty in the results. The entropy gives the absolute measure of uncertainty. This is called absolute because it does not take any reference data to measure the uncertainty. Entropy is the indirect method of accuracy assessment. Entropy method is used for accuracy measure when there are no references data are available for accuracy measurement. The higher entropy implies higher uncertainty and vice-versa in class identification on classified output. The advantage of entropy measure for accuracy assessment is also proven by Kumar and Dadhwal [34].

Study area

The study area selected for this research work is Sitarganj Tehsil which is located near the Pant Nagar under Uttarakhand state, India. Sitarganj's geographic lat/long extends from 28°53′57.12′′N to 28°56′31.22′′N latitudes and 79°34′22.92′′E to 79°36′35.27′′E longitudes. The 'G.B Pant University of Agriculture and Technology' is located in Pant Nagar which participated during green revolution of India. This is the first Agricultural University of India since 1960 and Pant Nagar is famous for this. For this research work Sitarganj has been selected as a study area because field work data as well as satellite images of Resourcesat-1 acquired on October 2007 was available. Also the images of Resourcesat-2 were acquired for the study area. The study area presents different land cover classes like Sal forest, Eucalyptus plantation, agricultural land with sugarcane and paddy as major crops and two water reservoirs namely, Bhagul reservoir and Dhora reservoir. The study area presents two types of edges or boundaries among the land cover classes. (a) The sharp distinct edges among the agricultures fields and (b) The boundaries which changes gradually from one class to another such as in water class water changes gradually to grass land.

Figure 2: Location of study area (*source*: Google Earth, accessed on 11th Jan 2013)

Data used

In this research work, AWiFS (Advanced Wide Field Sensor), LISS-III (Linear Imaging Self Scanner) and LISS-IV images from the Resourcesat-1 (Indian Remote sensing Satellite-P6) and the Resourcesat-2 (Indian Remote sensing Satellite-P6) satellites have been used (table 1).The images were acquired on the same date for each individual satellite. LISS-III and AWiFS images have been used for classification, whereas the finer resolution LISS-IV image has been used for the generation of reference data. Resourcesat-2 has an improved radiometric accuracy as compared to Resourcesat-1 and the developed classifier was tested on both datasets. Details of the sensors are explained below.

Table 1:

Satellite	Sensors	Acquiring Date
Resourcesat-1 (IRS P-6)	LISS-IV	15th October 2007
	LISS-III	
	AWiFS	
Resourcesat-2 (IRS P-6)	LISS-IV	23rd November 2011
	LISS-III	
	AWiFS	

Images used for this research work

The IRS-P6 (Resourcesat-1) satellite was launched by ISRO in October 2003. It is the 10th mission of Indian Remote Sensing (IRS) satellite series. The on-board sensors on this satellite are LISS-IV (Linear Imaging Self Scanner), LISS-III and AWiFS. Table (2) describes these sensors characteristics in details.

Table 2: Sensors specification of Resourcesat-1 and Resourcesat-2 (*source*: www.isro.org, accessed on 8th Jan 2013)

Specifications	LISS-IV		LISS-III		AWiFS	
	Resourcesat-1	Resourcesat-2	Resourcesat-1	Resourcesat-2	Resourcesat-1	Resourcesat-2
Spatial resolution (m)	5.8	5.8	23.5	23.5	56	56
Swath (KM)	23.9(MX Mode) 70.3(PAN Mode)	70.0 in MX mode and mono mode	141	141	740	740
Spectral Bands (microns)	0.52-0.59 0.62-0.68 0.77-0.86	0.52-0.59 0.62-0.68 0.77-0.86	0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70	0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70	0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70	0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70
Quantisation (bits)	7	10	7	10	10	12

IRS-P6 (Resourcesat-2) is the follow up mission of Resourcesat-1. In April, 2011 Resourcesat-2 was launched by ISRO. The on-board sensors are LISS-IV, LISS-III and AWiFS. The major changes in RESOURCESAT-2 as compared to RESOURCESAT-1 are: improved radiometric accuracy from 7 bits to 10 bits for LISS-III and LISS-IV and 10 bits to 12 bits for AWiFS [42].

Formulation of FCM Objective function to incorporate contextual information

To solve a problem using MAP-MRF it is important first to formulate the objective function. Here, the objective function of FCM has been formulated for the smoothness prior and for discontinuity adaptive priors that are able to incorporate contextual information. The objective function is similar to the objective function of FCM except for the inclusion of neighbourhood information.The objective function of FCM is given in equation (1),

$$J_m(U,V) = \sum_{j=1}^{N}\sum_{i=1}^{c} \mu_{ij}^{m} \|X_j - V_i\|^2, \quad 1 \le m < \infty \tag{1}$$

The objective function in (1) calculates the membership values for pixels based on spectral properties, but it does not include spatial contextual information. Below, objective functions have been formulated that incorporate spatial contextual information using either the smoothness prior or discontinuity adaptive priors.

Equation (2) states the FCM objective function formulated using smoothness prior. From now onwards the objective function in equation (2) will be referred as FCM-S.

$$U(\mu_{ij}|d) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\mu^{m}{}_{ij}\, d^2{}_{ij}\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\sum_{j' \in N_i}\beta\left(\mu_{ij}-\mu_{ij'}\right)^2\right] \quad (2)$$

where,

$U(\mu_{ij}|d)$ = Posterior energy of image μ, given image d.

λ = Weight for spectral and contextual information (smoothness strength).

μ_{ij} = Membership value of pixel i of class j.

N = Number of pixels.

m = weighing exponent

$d^2 = |d_i - c_j|^2$; d_j =vector pixel value, c_j = mean vector of class j.

β = weight for neighbors.

N_i = Neighborhood window around pixel i.

In Equation (2) spectral information has been included by using the objective function of FCM and spatial contextual information was incorporated by using smoothness prior.

Let η, be defined as $\mu_{ij} - \mu_{ij'}$ i.e. the difference between target pixels (pixel i) membership value and the membership of its neighboring pixels membership value in a neighborhood system N_i. Then

$$U(\mu_{ij}|d) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\mu^{m}{}_{ij}\, d^2{}_{ij}\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\sum_{j' \in N_i}\left(-\gamma e^{-\frac{\eta^2}{\gamma}}\right)\right] \quad \textit{Equation (3)}$$

$$U(\mu_{ij}|d) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\mu^{m}{}_{ij}\, d^2{}_{ij}\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\sum_{j' \in N_i}\left(-\frac{\gamma}{1+\frac{\eta^2}{\gamma}}\right)\right] \quad \textit{Equation (4)}$$

$$U(\mu_{ij}|d) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\mu^{m}{}_{ij}d^{2}{}_{ij}\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\sum_{j'\in N_i}\left(\gamma\ln(1+\frac{\eta^2}{\gamma})\right)\right] \quad \textit{Equation (5)}$$

$$U(\mu_{ij}|d) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\mu^{m}{}_{ij}d^{2}{}_{ij}\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{c}\sum_{j'\in N_i}\left(\gamma|\eta|-\gamma^2\ln(1+\frac{|\eta|}{\gamma})\right)\right] \quad (6)$$

where, all the symbols have common meaning. In addition, γ is the AIF, with a value varying between 0 and 1. Adaptive potential functions (APF) have been used in equations (3) - (6) to formulate the objective function of FCM with discontinuity adaptive priors. From now onwards, the objective functions mentioned (3) - (6) will be referred as FCM-DA (H1), FCM-DA (H2), FCM-DA (H3) and FCM-DA (H4) respectively.

Simulated Annealing and Gibbs sampling algorithm

Simulated annealing (SA) was first introduced by Metropolis *et.al* [43] to simulate particle behavior in a thermal equilibrium. SA is a stochastic relaxation algorithm to determine the global minimum solution. The idea of SA is similar to a process of metallurgy where the metal is heated up to a certain limit to reconstruct it in a desired shape. Then the metal is cooled down very slowly so that it gets enough time to respond. The SA algorithm is frequently used in MRF based image analysis to find the global optimum solutions [3], [4], [5]. Here SA is used to find optimum global energy function.

The SA algorithm designed by Geman and Geman [3] is known as the Gibbs sampler. It generates new membership values for each pixel. In order to do so, it depends upon a parameter *T,* called the temperature*.* SA starts with a high value of *T* and then the value of *T* is decreased according to specific criteria, called the cooling schedule. The process runs till the value of *T* reaches zero. In this work the cooling schedule given by Dubes and Jain has been used as mentioned in Equation (7).

$$T_{k+1} = \frac{\ln\,(1+k)}{\ln\,(2+k)}T_k \quad (7)$$

The temperature cooling function mentioned in equation (7) has been used here because it decreases the temperature *T* faster than other existing methods [6].

Parameters to be estimated

The objective functions mentioned in equations (3) - (6) involves the parameters as listed below. It is necessary to estimate the parameters before the objective functions can use for classification [5]. The following parameters have been optimized.

(a) Fuzzifier (*m*)

(b) Initial (T_0) and final temperature (T_f)

(c) Lambda (λ)

(d) Beta (β)

(e) Gamma (γ)

There are no standard methods to estimate the parameter. Several method such as RMSE, total energy etc. have been used in the past to estimate these parameters [40],[44]. In this work, estimation of parameter has been conducted using the entropy method [33]. The entropy method gives an absolute measure of uncertainty and at the same time edge preservation is also checked by mean and variance method to estimate the parameters. The Entropy method is discussed in section 5.5.3 and the mean and variance method for edge preservation is discussed in detail in section 5.4.

Methods adopted for accuracy assessment

Accuracy assessment of classified output is necessary to obtain the quality of the results. In this work where an image to image based accuracy assessment technique has been used, the accuracy of the classification of a coarser resolution images was evaluated with the classified output of a finer resolution image. In this section, accuracy assessment techniques for the sub-pixel classified outputs that have been used for this research work are described.

Fuzzy Error Matrix

To assess the accuracy of a classified output, the testing samples from classified fraction output and the reference data from actual class were collected. Using these test samples a fuzzy error matrix was generated using the specific operator as in equation (9). The columns represent the actual classes from the reference data, while rows represent the classes of the classified data. In this matrix the diagonal elements indicate the classes which are correctly classified and the off-diagonal elements indicate the misclassified classes. Fuzzy Error Matrix (FERM) [9] is similar to a conventional error matrix. The conventional error matrix takes hard classified images as input whereas FERM takes fraction images as its input. In FERM the elements of the matrix are calculated based on the fuzzy set theory [1]. It uses the 'MIN' operator (8), which identifies the maximum possible overlap between reference and classified datasets. The MIN operator is known as fuzzy set intersection operator [10].

$$\min\left(S_{nk}, r_{nl}\right) \tag{8}$$

where, S_{nk} is the membership grade of class k at pixel n for the assessed dataset.

r_{nl} is the membership grade of class k at pixel n for the reference dataset.

Sub-pixel confusion uncertainty matrix

A new cross comparison matrix was proposed by Silvan-Cardenas and Wang [10] that used confusion interval in the form of plus-minus maximum error to measure the sub-pixel accuracy. This new error matrix is referred to as sub-pixel confusion uncertainty matrix (SCM). It uses composite operator namely 'MIN-LEAST', 'MIN-MIN' and 'MIN-PROD'. These operators are described below.

- The MIN-MIN composite operator is formed by one single operator i.e. MIN operator. For both diagonal and off-diagonal elements this composite operator uses the minimum operator. This operator assigns diagonal elements in a first step and then it calculates the off-diagonal elements based on the over and underestimation errors [10].
- The MIN-LIST composite operator is formed by the two basic operators MIN and LEAST. Here the MIN operator is for the diagonal cells and the LEAST operator is for the off-diagonal cells. The MIN operator measures the maximum sub-pixel overlap among the classes and the LEAST operator measures the minimum possible sub-pixel overlap between two classes [10]. This MIN-LEAST operator creates a diagonal matrix for a perfect matching case [10].

- The MIN-PROD composite operator was proposed by Pontius and Cheuk [32]. It uses the MIN operator for the diagonal cells and PROD operator for the off-diagonal cells. The diagonal cells give the maximum overlap between the reference and assessed classes. The off-diagonal cells measure the expected overlap of reference and assessed classes.

Entropy method

Classification accuracy is generally measured by an error matrix, but for this work generation of reference data for LISS-IV image was not possible because of the unavailability of further higher resolution image for the study area as well as it is not possible to generate fraction reference output from ground with large number of samples. In such case entropy [33] is used as an absolute measure of uncertainty. Entropy calculates the uncertainty from the classified data without using any external data so it is an indirect method to measure accuracy. The entropy of a classified fraction output can be calculated by equation (9). For a better classified output the entropy at known class will be low and at unknown class it will be high in a fraction image. For example if we take fraction image of crop, the entropy value at crop will be low whereas entropy value other than crop location will be high. Thus low uncertainty implies more accurate classified output and vice-versa. The mathematical formula for entropy is given in equation (9).

$$Entropy\ (x) = \sum_{i=1}^{c} -\mu(w_i/x)\log_2(\mu(w_i/x)) \tag{9}$$

where, c is the total number of classes and $\mu(w_i/x)$ is the estimated membership function of class i for pixel x.

For high uncertainty the value of entropy in equation (9) is high and inverse. Entropy is defined based on actual output of classifier so it can give the pure uncertainty of the classification results [33]. In this research work entropy has been used combining with other measures to optimize the parameters of MRF.

Conclusion

The main objective of this research work is to develop a sub-pixel classifier for classifying moderate and coarse spatial resolution multi-spectral dataset using FCM and DA MRF models. Another objective is to study the four DA models for FCM. The efficiency for DA model would be chosen after measuring the accuracy. In this research work a method we are aiming to incorporating spatial contextual information in FCM using DA MRF models which preserves the edges.

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