CLASS BASED RATIOING EFFECT ON SUB-PIXEL SINGLE LAND COVER AUTOMATIC MAPPING

Anil Kumar[1*a], Suresh Saggar[b],

[a]Indian Institute of Remote Sensing, Dehradun, anil@iirs.gov.in
[b]Birla Institute of Technology & Science, Pilani (Rajasthan), suresh.saggar@gmail.com

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ABSTRACT:

Sub-pixel based digital image classification outputs from coarse spatial resolution remote sensing images can be closer to ground information as compared to hard classification outputs. This has been proven from work published by different researchers in last decade. In sub-pixel based classification output, each pixel represents a class in the form of end member or membership value.
Fuzzy classification approach may be beneficial where a mixed pixel may be assigned multiple class memberships. Fuzzy approaches may be applied as supervised and unsupervised classification approaches. With different disasters coming around the world, disaster management professionals may be interested to extract only one land cover class of interest affected in disaster from remote sensing data. In conventional approach for extracting land cover classes; all the classes present in the area have to be identified first, then single class of interest can be taken out from the classified data. The conventional classification approaches will give error if all the classes present in the area have not been identified properly. Neural network classifier can be trained to extract single class of interest from remote sensing data. The successful implementation of neural network classifier depends on a range of parameters related to the design of the neural network architecture. Moreover, neural networks are very slow in the learning phase of the classification, which is a serious drawback when dealing with images of very large size. Further, besides their complexity, neural networks are restricted to the analysis of data that is inherently in numerical form. In this work it has been tried to apply fuzzy set theory based sub-pixel classifiers for extracting single class of interest. The use of fuzzy set based classification methods in remote sensing have evoked growing interest for their particular value in situations where the geographical phenomena are inherently fuzzy. While studying Fuzzy c-Means (FCM) as well as Possibilistic c-Means (PCM) for extraction of single class of interest, it has been found that PCM can be used for single class extraction of interest. In this work water class has been identified for single class extraction. A well known problem of merging of shadow pixels with water class was encountered in this work. To overcome this problem, remote sensing sensor independent class based ratioing data has been generated. Class based ratioing data has been taken as input in PCM classifier, and water class has been identified at sub-pixel level. The input data was used from IRS-P6 LISS-III sensor and testing data as fraction image generated from IRS-P6 LISS-IV sensor. The output from this work was evaluated using fuzzy error matrix (FERM) and found overall accuracies 93.4% and 95.3% respectively for both sub scenes. For this work, a module in in-house SMIC package was developed in JAVA environment by the authors. It has been observed while incorporating class based ratioing data in PCM based sub-pixel classifier, effect of pixels having varying illuminations due to shadow within class was minimized (Figure 1). It was also observed from this approach that shadow pixels were not mixing with water class pixels.

1. INTRODUCTION

Digital image classification is a fundamental image processing operation to extract land cover information from remote sensing data and it assigns a class membership for each pixel in an image. Land cover information can be extracted using crisp as well as fuzzy classification approaches. In a crisp classification, each image pixel is assumed to be pure and is classified to one class. Often, particularly in coarse spatial resolution images, the pixels may be mixed containing two or more classes. Fuzzy classifications may be beneficial where a mixed pixel may be assigned multiple class memberships. Fuzzy approaches may be applied as supervised and unsupervised classification approaches.

To identify a feature of interest not only have to classify individual pixels as belonging to a specific class such as soil, vegetation or water but also identify a set of such pixels as a part of the feature. In number of applications there may be requirement for extracting only one land cover class from remote sensing multi-spectral images, at sub-pixel level. In the past many learning algorithms like neural network has been used for performing classification to extract land cover class from remote sensing image and it can be used for single class extraction at sub-pixel level (Aziz, 2004). For example, feature extraction for multi-source data classification with artificial neural networks (Benediktsson and Sveinsson, 1997), the Hopfield neural network as a tool for feature tracking and recognition from satellite sensor images (Côté and Tatnall, 1997), remote sensing image analysis using a neural network and knowledge-based processing (Murai and Omatu 1997). The successful implementation of neural network classifier depends on a range of parameters related to the design of the neural network architecture (Arora and Foody, 1997). Moreover, neural networks are very slow in the learning phase of the classification, which is a serious drawback when dealing with images of very large size. Further, apart from their complexities,

*Corresponding Author

neural network are restricted to the analysis of data that is inherently in numerical form.

In this paper fuzzy logic based algorithm, which is independent of statistical distribution assumption of data, has been studied to extract single land cover class from remote sensing multi-spectral images. As the images are affected, by undesirable effects on the recorded radiances caused by variations in topography has been removed by class based sensor independent ratioing at preprocessing stage. Possibilistic c-Means algorithm for this work has been implemented in such a manner that remote sensing image from any sensor can be used for single class extraction. For this work ALCM: Automatic Land Cover Mapping module has been used from JAVA based in-house image processing package, named as SMIC: Sub-Pixel Multi-Spectral Image Classifier (Kumar et al., 2006).

2. IMAGE RATIOING AND CLASSIFICATION APPROACHES

The process of dividing the pixels in one image by the corresponding pixels in a second image is known as ratioing. It is one of the most commonly used transformations applied to remotely sensed images. There are two reasons why this is so. One is that certain aspects of the shapes of spectral reflectance curves of different earth-surfaces cover types can be brought out by ratioing. The second is that undesirable effects on the recorded radiances, such as that resulting from variable illumination caused by variations in topography, can be reduced. In this work class based sensor independent ratioing has been applied by the following function;

$$Ratio\ \mathrm{Im}age_{(I)} = \frac{Maximum_{(I)}}{Minimum_{(I)}}$$

Where I is class of interest;

Class based ratio image of each class was used as an input in fuzzy set theory based classifiers. From the description of the fuzzy logic based sub-pixel classification algorithms, Fuzzy c-Means (FCM) and Possibilistic *c*-Means (PCM) (Krishnapuram and Keller, 1993) approaches have been studied.

Fuzzy *c*-Means (FCM) is basically a clustering technique where each data point belongs to a cluster to some degree that is specified by a membership grade, and that the sum of the memberships for each pixel must be unity (Bezdek, 1981). This can be achived by minimizing the generalized least - square error objective function;

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{c}(\mu_{ij})^m \| X_i - v_j \|_A^2 \qquad (1)$$

subject to constraints;

$$\sum_{j=1}^{c}\mu_{ij} = 1 \text{ for all i}$$

$$\sum_{i=1}^{N}\mu_{ij} > 0 \text{ for all j}$$

$$0 \le \mu_{ij} \le 1 \text{ for all i, j}$$

where Xi is the vector denoting spectral response of a pixel i, vj is the collection of vector of cluster centers of a class j, μij is class membership values of a pixel, c and N are number of clusters and pixels respectively, m is a weighting exponent (1<m<∞), which controls the degree of fuzziness, $\| X_i - v_j \|_A^2$ is the squared distance (d_{ij}) between X_i and v_j, and is given by;

$$d_{ij}^2 = \| X_i - v_j \|_A^2 = (X_i - v_j)^T A (X_i - v_j) A \qquad (2)$$

where A is the weight matrix.

Amongst a number of A-norms, three namely Euclidean, Diagonal and Mahalonobis norm, each induced by specific weight matrix, are widely used. The formulations of each norm are given as (Bezdek, 1981),

Euclidean Norm $A = I$

Diagonal Norm $A = D_j^{-1}$

Mahalonobis Norm $A = C_j^{-1}$

where I is the identity matrix, Dj is the diagonal matrix having diagonal elements as the eigen values of the variance covariance matrix, Cj given by;

$$C_j = \sum_{i=1}^{N}(X_i - v_j)(X_i - v_j)^T \qquad (3)$$

In this research work value of weighting exponent m has been taken as 2.2 and Euclidean Norm of weight matrix A has been taken, as it givens maximum classification accuracy compare to other weighted norms (Aziz, 2004).

The class membership matrix μij is obtained by;

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}^2}{d_{ik}^2}\right)^{1/(m-1)}} \qquad (4)$$

where, $d_{ik}^2 = \sum_{j=1}^{c} d_{ij}^2$;

The original FCM formulation minimizes the objective function as given in equation (1).

subject to $\sum_{j=1}^{c} \mu_{ij} = 1$ for all i

But in PCM one would like the memberships for representative feature points to be as high as possible, while unrepresentative points should have low membership in all clusters (Krishnapuram and Keller, 1993). The objective function, which satisfies this requirement, may be formulated as;

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{c} (\mu_{ij})^m \parallel X_i - v_j \parallel_A^2 + \sum_{j=1}^{c} \eta_j \sum_{i=1}^{N} (1-\mu_{ij})^m$$

(5)

Subject to constraints;

$\max\limits_{j} \mu_{ij} > 0$ for all i

$\sum_{i=1}^{N} \mu_{ij} > 0$ for all j

$0 \le \mu_{ij} \le 1$ for all i, j

here μ_{ij} is calculated from equation (4).

In equation (5) where ηj is the suitable positive number, first term demands that the distances from the feature vectors to the prototypes be as low as possible, whereas the second term forces the μij to be as large as possible, thus avoiding the trivial solution. Generally, ηj depends on the shape and average size of the cluster j and its value may be computed as;

$$\eta_j = K \frac{\sum_{i=1}^{N} \mu_{ij}^m d_{ij}^2}{\sum_{i=1}^{N} \mu_{ij}^m} \tag{6}$$

where K is a constant and is generally kept as one. After this, class memberships, μij are obtained as;

$$\mu_{ij} = \frac{1}{1 + \left(\dfrac{d_{ij}^2}{\eta_j} \right)^{1/(m-1)}} \tag{7}$$

3. SUB-PIXEL AUTOMATIC SINGLE LAND COVER CLASS EXTRACTION

For extracting land cover classes, FCM is depended upon number of land cover classes to be extracted from remote sensing multi-spectral image. This can be seen from membership values generated from equation 4, are depended upon summation of distances of unknown feature to mean vectors of land cover classes ($d_{ik}^2 = \sum_{j=1}^{c} d_{ij}^2$). When extracting only one land cover class, in that case $d_{ik}^2 = d_{ij}^2$ and than μ_{ij} for all features becomes one. This concludes that all features in a remote sensing multi-spectral image belongs to one class, which is not the case. While working with PCM algorithm for extracting single land cover class it behaves as follows;

$d_{ik}^2 = d_{ij}^2$ while extracting single land cover class; and μ_{ij} =1 for class features from equation (4) and

$\sum_{i=1}^{N} \mu_{ij}^m = N$ in equation (6)

So, $\eta_j = K \dfrac{\sum_{i=1}^{N} d_{ij}^2}{N}$ from equation (6).

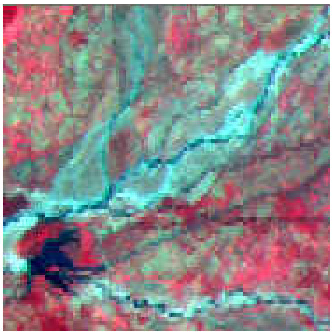
And now from equation (7) μ_{ij} will be calculated;

This indicates that possibilistic view of the membership of a feature vector in a class has nothing to do with its membership in other classes (Krishnapuram and Keller, 1993).

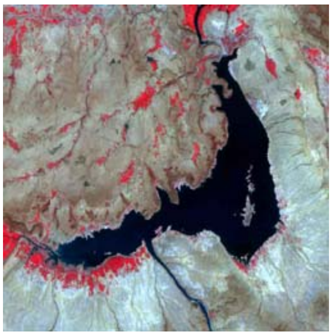
4. TEST DATA USED

Test data sets for this work have been acquired from AWIFS sensor of IRS-P6 satellite over two different sites of India (figure 1) like; Asan reservoir (Dehradun District) (Center coordinates 77^{O} 40$'$ 05.36$''$ E, 30^{O} 26$'$ 08.00$''$ N, Acquisition date 4th November 2003) and Rana Pratap Sagar Dam (Kota Distirct, Rajasthan state) (Center coordinates 24^{O} 47$'$ 30.18$''$ N, 75^{O} 34$'$ 14.77$''$ E, Acquisition date 18th February 2004). All the data sets were geo-referenced and all the four bands of these data sets were used with spatial resolution of 56 m. Major land cover classes present in these area are water, forest, fallow land, sand, crop land and settlement. The one class of interest, namely, water was studied for discrimination with background.

Separate sample data sets were used as training as well as testing stage. The size of training data used for supervised sub-pixel classification approach was approximately equal to 10n (Jensen, 1996), were n is dimension (number of bands) of data used. In this work it has been tried to study the performance of PCM algorithm for extraction of single land cover class at sub-pixel classification with small training data set. The numbers of pixels used at training stage are given in table 1. These pixels were collected from Rana Pratap Sagar Dam image only and same training data set was used for other image also. For testing the classification accuracy reference fraction images were used from LISS-III sensor of IRS-P6 satellite for both the data sets of same dates as of AWIFS data (figure 2). A total of 500 testing pixels for class water were randomly selected, from corresponding outputs and their reference images respectively, which are significantly larger than the sample size of 75 to 100 pixels per class as recommended by Congalton (1991) for accuracy assessment purpose. The accuracy assessment of sub-pixel classification output has been done using Fuzzy Error Matrix (FERM) (Binaghi *et al.*, 1999).



a) Asan reservoir

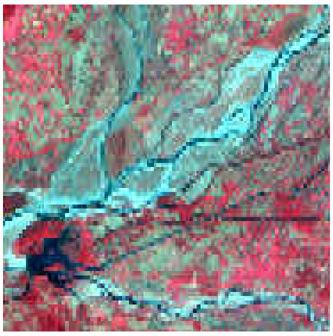


b) Rana Pratap Sagar Dam

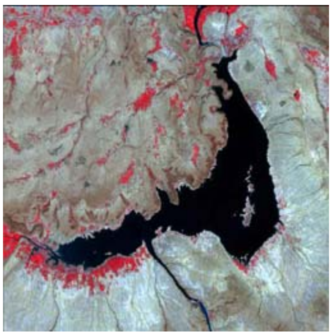
Figure 1. FCC images of test sites from AWIFS sensor

Sl. No.	Type of data used	No. of pixel used
1.	Training data	
	Water	41

Table 1. Details of training data set



a) Asan reservoir



b) Rana Pratap Sagar Dam

Figure 2. Reference FCC images of test sites from LISS-III sensor

5. DISCUSSION AND CONCLUSION

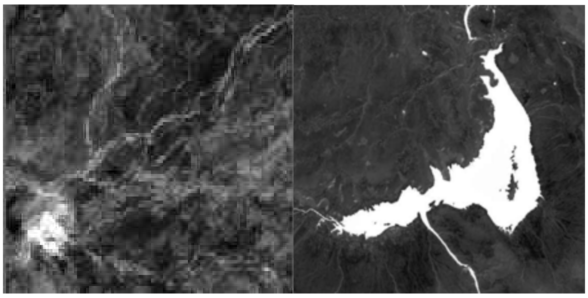
In this paper, we have presented a special form of PCM algorithm while extracting single land cover class from multi-spectral remote sensing images. For this the ALCM module from, SMIC: Sub-Pixel Multi-Spectral Image Classifier package (Kumar et al., 2006) has been used. The ALCM module has capability to process multiple multi-spectral images for single land cover class extraction at sub-pixel level using supervised approach. The module detects multi-spectral images of same bands by decoding the header files in generic BIL format and then reads all the images. All these images can be processed using PCM single land cover class extraction algorithm using training data. At the output, two options are available, first, where a threshold is provided to identify pixels having membership greater than some specific membership value of that single land cover class or second option is without a threshold. While using PCM approach for single land cover class extraction, its variables appear differently in comparison of multiple land cover class extraction. In single land cover class extraction case;

$d_{ik}^2 = d_{ij}^2$; and μ_{ij} =1 for class features from equation (4),

so, $\eta_j = K \frac{\sum_{i=1}^{N} d_{ij}^2}{N}$ from equation (7).

Which is not the case while extracting multiple land cover class extraction using PCM method. From table 2, it is clear that user, producer as well as over accuracy of single land cover class water were found very high. As in figure 3, upper stream of Asan reservoir membership values were found in the range of 0.890 to 0.996. In down stream of river membership values for land cover class water were of the range 0.842. In another data set; Rana Pratap Sagar Dam scene, upper stream of water body have membership value in the range 0.996. Thus, it can be concluded that water quality in both the two sites is more or less same. Membership values of the fraction images may be correlated with ground data to extract turbidity of water, lentic and lotic water bodies, etc. Due to sub-pixel classification water component in some of the other land cover classes were found of small membership values. This indicate that sub-pixel classification is very much good to classify remote sensing multi-spectral data having vagueness in the data sets. While incorporating class based ratioing data shadow effect has been minimized in classification output. Due to class based rationing data shadow areas did not merge with class water. Further, ALCM module approach will be very much helpful were there is an urgent need of processing multiple multi-spectral images for single class extraction at sub-pixel level, specifically in flood prone areas and risk analysis.

Presently this module has limitation to incorporate training data from different input multiple multi-spectral images. To incorporate training data from different input multiple multi-spectral images will definitely improve the sub-pixel classification accuracy of single land cover class extraction, which needs to be examined further.



a) Asan reservoir   b) Rana Pratap Sagar Dam

0   μ   1   μ = Membership Value

Figure 3. Single class water extracted from test data sets using AWIFS Images

Sub-Pixel Classification Accuracy	Data of Asan reservoir		Data of Rana Pratap Sagar Dam
User's Accuracy (%)	Water	93.3	95.4
Producer's Accuracy (%)	Water	93.7	97.1
Overall Accuracy (%)	93.7		97.1

Table 2. User's, Producer's and Overall Accuracies for different data sets.

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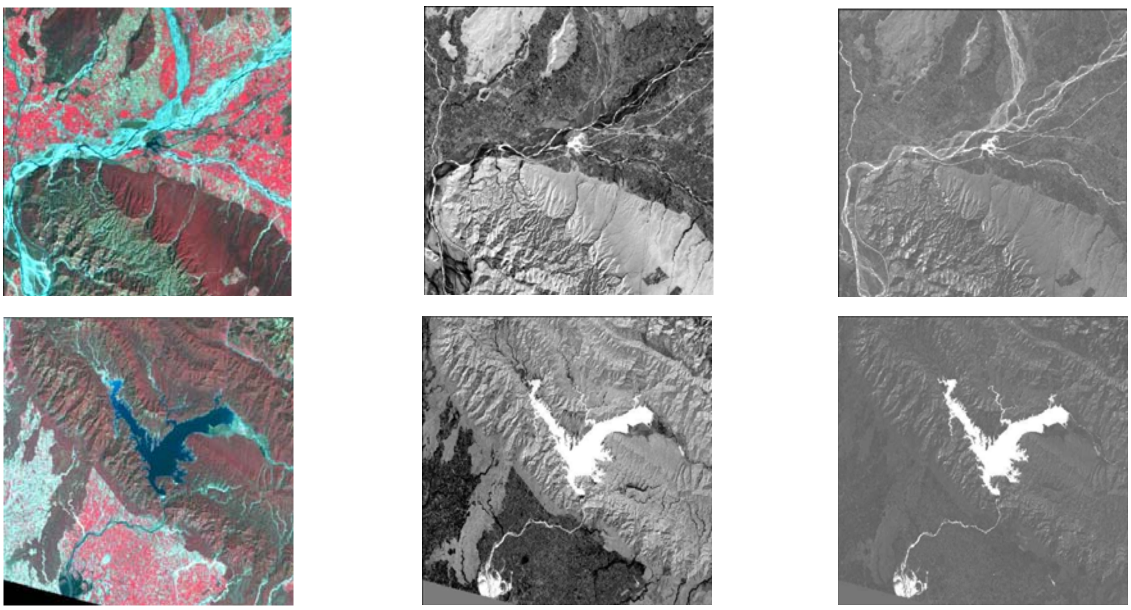

a) Raw Image   b) Single class without class based ratioing input   c) Single class with class based ratioing input

Figure 1: Single class water extracted using PCM classifier