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An Automated Process for Crop Discrimination through Temporal Analysis

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Abstract—*This paper reviews an automated tool for soft-classifier based approach for specific crop discrimination with the help of temporal data set. For testing the tool, temporal FORMOSAT-2 data have been used for identification of rice crop using PCM approach in supervised mode for sub-pixel classification. The PCM classification method decomposes the pixel into class proportions. The developed tool tried to automate the variables in identification of specific crop from temporal multi-spectral remote sensing data. The use of temporal image data helps to identify specific crop as the temporal evolution of the spectral responses of the different vegetated classes.*

Keywords*: Remote sensing data, Temporal analysis, Soft-classification approach, Indices, Possibilistic c-means (PCM).*

1. INTRODUCTION

The use of remote sensing images for identification and mapping specific crops has increased rapidly in the last few decade. For specific crop discrimination, multi-spectral images are used. The use of remotely sensed images for crop identification is essential due to the use of remote sensing images as an input for agriculture and private agencies [2] as this would provide time and cost efficient way to monitor and manage crop production and identification.

Identification of specific crop can not be done using just one date image data due to the overlapping of spectral information of various crops. This is due to the spectral overlapping of different crops/vegetation in specified data date. In this situation, it becomes a challenge to extract single class of interest because two or more crops overlapped. Temporal data images are helpful to resolve this issue. Temporal analysis includes acquisition of various images of same area on timely basis and then temporal profile of specific crop to be used in crop discrimination.

In specific crop discrimination, the specific crop growth area is identified using various methods that allow correct discrimination of specific crop using remote sensing data [4]. Conventionally in remote sensing one pixel is assigned to one class which is known as 'hard' or 'crisp' classification method [3]. Often, particularly in coarse spatial resolution images the pixel may be mixed containing two or more classes [1]. In such cases, the traditional hard classification method is not suitable because in hard classification method, the membership values are not lie between 0 and 1. To handle mixed pixel problem another classification approach known as soft classification adopted which decomposes the pixel into class proportions. Mixed pixels are normally found in boundaries between two or more mapping units, along gradients etc. when the occurrence of any linear or small sub-pixel object takes places [8]. Therefore fuzzy soft classification technique can be a best technique for extracting the single class of interest.

There are various soft fuzzy based classifier used for single class identification including ANN (Artificial Neural Network), SVM (Support Vector Machine), PCM (Possibilistic c-means) etc [7]. ANN can extract single class but it exhibits generalization problem. ANN provides good result for known pixels but in case of unknown pixel, the results are not satisfactory. Also in ANN as the dimension of an image increases the structure becomes complicated.

SVM is also a good choice while extracting specific crop identification. It gives good results but the problem of SVM is that it requires leaning.

PCM fuzzy based classifier is capable to extract single class with minimum training data set and less processing time. PCM is a modified form of FCM (Fuzzy c-Means). FCM can not identify single class as it follows probabilistic constraint. PCM assigns representative feature points the highest possible membership while unrepresentative points get low memberships [6].

The other unique feature of PCM is its non-confirmation to the probability rule that requires the sum of memberships of all classes in a pixel to be unity. This means that in the PCM classification technique the membership assigned to a class in a pixel is independent of the memberships assigned to other classes in the pixel [8]. Hence PCM can be effectively used for extracting single class of interest from an image.

2. TEMPORAL DATA PROCESSING APPROACH

Indices

Indices are basically used to produce temporal indices data. To enhance the vegetation signal in remotely sensed data and provide an approximate measure of green vegetation amount, a number of spectral vegetation indices have been proposed by combining data from multiple bands into single value [5]. The another main reason of generating indices data is to eliminate various albedo effect.

Vegetation indices incorporated in the tool has been listed in the table (1):

Table 1: Indices used in the tool

VEGETATION INDEX	EQUATION
Ratio Vegetation Index(RVI) or Simple Index(SI)	$\rho_{red} - \rho_{nir}$
Normalized difference Vegetation Index(NDVI)	$(\rho_{nir} - \rho_{red})/(\rho_{nir} + \rho_{red})$
Triangular Vegetation Ratio(TVR)	$0.5(120(\rho_{nir} - \rho_{red})-200(\rho_{nir} + \rho_{red}))$

Classification Approach

The objective of classification is to classify each pixel into one and only one land cover class (i.e. hard classification) or to estimate the partial membership of the classes in a pixel(i.e. soft classification). To classify remote sensing images into various land cover types different classification methods have been developed.

The main concern of this section is description of fuzzy based classifier for recognition of single class of interest. PCM is a well-known method for crop discrimination. PCM is a generalized form of FCM in which each data point belongs to a cluster with some degree that is specified by a memberships for each pixel be one [1].

In PCM the membership for representative features points to be as high as possible, while unrepresentative points should have low membership in all clusters [6]. The objective function can be formulated in equation (1) with constraints in equation (2)-(4):

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{c}(\mu_{ij})^m \, \| X_i - V_j \|_A^2 + \sum_{j=1}^{c}\eta_j \sum_{i=1}^{N}\left(1-\mu_{ij}\right)^m \quad (1)$$

subject to constraints;

$$\text{for all } i \ \max_j \mu_{ij} > 0 \quad (2)$$

$$\text{for all } j \ \sum_{i=1}^{N} \mu_{ij} > 0 \quad (3)$$

$$\text{for all } i,j \ 0 \le \mu_{ij} \le 1 \quad (4)$$

where

N is the total number of the pixels,

μ_{ij} is the membership of pixel i in class j,

m is the weighted constant ($1 < m < \infty$),

V_j is the cluster centre for class j,

X_i is the feature vector for pixel i,

A is the weight matrix and Euclidean norm used here,

η_j is parameter that is dependent on the shape and average size of cluster j and is computed according to equation (5):

$$\eta_j = K \frac{\sum_{i=1}^{N} \mu_{ij}^m d_{ij}^2}{\sum_{i=1}^{N} \mu_{ij}^m} \quad (5)$$

where K is a constant generally kept as unity.

There after class membership values μ_{ij} were calculated according to equation (6):

$$\mu_{ij} = \frac{1}{1+\left(d_{ij}^2/\eta_j\right)^{1/(m-1)}} \quad (6)$$

3. TEST DATA AND STUDY AREA

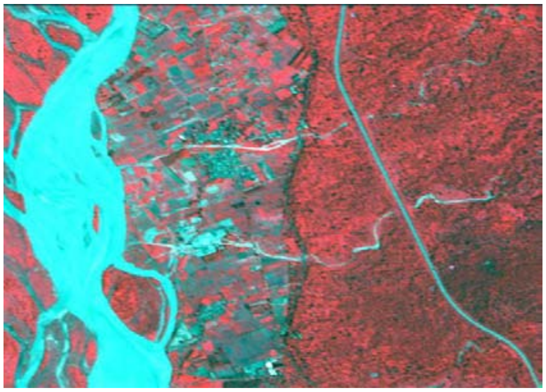
Test data used in this study was temporal in nature and acquired from FORMOSAT-2 sensor. FORMOSAT-2 is the first medium resolution satellite developed by NSPO (NATIONAL SPACE ORGANIZATION). This satellite is able to revisit the same point on the globe everyday in the same viewing conditions. FORMOSAT-2 features optical sensors with 2-meter panchromatic and 8-meter multispectral (i.e. blue, green, red, near-infrared) resolution. The images captured by the satellite can be used for land distribution, natural resources research, forestry, environmental protection, disaster prevention, rescue work, and other applications.

The details of multi-spectral temporal data set used for crop identification has been listed in the table (2):

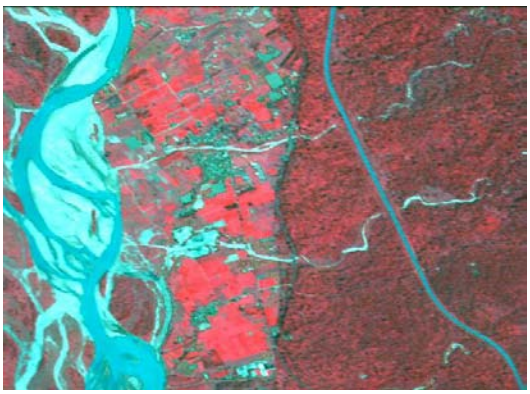
Table 2: Temporal data set details

FORMOSAT-2(8m)
08-August-2014
25-September-2014
13-October-2014
03-November-2014
04-December-2014

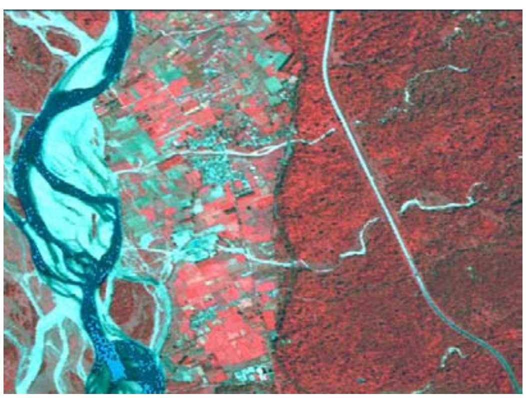
The area taken for this study was Chandipul region (29°56’37’’N, 78°9’59S) and its surroundings in Haridwar as shown in Fig. 1. In Haridwar district, the area under rice is comparatively higher than other crops. Here remotely sensed temporal images were used for crop discrimination because of overlapping of spectral information of one crop with other crops. Total five scenes from august to December 2014 were considered for current study area shown in Fig. (1):



08-August-2014



25-September-2014



13-October-2014

03-November-2014

04-December-2014

Fig. 1: Scenes considered for study

4. METHODOLOGY

The methodology used for specific crop discrimination is broadly divided into four steps. The sequence of steps has been shown in Fig. 2:

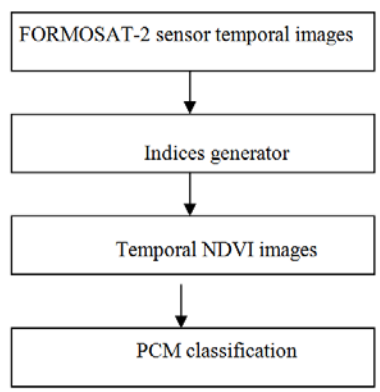


Fig. 2: Images processing methodology

To make the PCM classification method automated, the value of ‘m’ which controls the degree of fuzziness among pixels was not fixed instead it was tried to control the value of ‘m’ indirectly with the help of Error Threshold value. The Error Threshold value was specified as 125 for this tool because based on ground information, the difference between known and unknown pixel must be higher than 100-125 on 0-255 scale as output was stored on this scale.

The condition which contributes to optimize 'm' automatically was 'Delta>= Error Threshold Value' where delta was the average of the difference from class of interest say favorable class to all other classes say unfavorable classes. In each iteration the value of 'm' decreased by the rate specified by the user.

5. GENERATION OF OUTPUTS

The output from the developed tool can be generated in soft classification. The output of specific crop identification (rice in this study) using the five temporal scenes shown in Fig. (1), was depicted in Fig. (3). In output, the pixel values were represented between 0 to 1 membership values.

The circled area in Fig. 2 shows rice crop which was discriminated with the help of other temporal images. For finding the specific crop it is necessary to have a temporal data set (remote sensing images) but it is also required that the dates of images should be within the time of crop growth cycle.

0 μ 1

μ = Membership Value

Fig. 2: Final output

6. CONCLUSION

The main objective of developing an automated tool for specific crop identification was to help various industries and government for better decision making process. The developed tool provides the cost and time effective ways to discriminate specific crop using temporal data set. The tool has been developed in Java environment, so it is platform independent. The developed tool can be extended by incorporating various other specific crop identification methods in it.

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