COMPUTER UNDERSTANDING OF SUB-PIXEL LAND COVERS

Jayanta Kumar Ghosh.
Research Scholar. Civil Engineering Department.
University of Roorkee. Roorkee. UP. 247 667. INDIA.

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ABSTRACT

Sub-pixel analysis of satellite data is important for accurate information and estimation of the different land cover classes. This paper defines a new method for direct classification and estimation of the sub-pixel land covers. It is a fuzzy knowledge based approach wherein features (LINGUISTIC VARIABLES) are addressed by fuzzy labels. This approach can be utilised in developing an image understanding system.

1. INTRODUCTION

In satellite images, land cover classes are classified with a certain degree of uncertainity, especially when mixed pixels occur. This is due to their continuous spatial coverage rather than abrupt and inter-grade gradually. Thus, mixed pixels occur in a satellite image either at the boundaries of the cover types or due to the sub-pixel phenomena *(Fisher and Pathirana, 1990).* Previous studies show that different classification methods for classifying or assigning labels to pixel may achieve classification accuracy greater than 85% for "pure" pixels but less than 75% correct classification for regions having mixed pixels *(Metzler and Cicone, 1983).* This is due to the fact that the mixed pixel displays a composite spectral response which may be dissimilar to each of its component classes *(Campbell, 1987).* Thus, due to the inherent presence of mixed pixel, classification schemes are prone to errors.

To get through the crux, a number of approaches, basically statistical in nature, have been developed and tested to unmix the pixels into their constituent classes *(Settle and Drake 1993, Jasinski and Eagleson 1990, Fisher and Pathirana 1990).* Typically, pixel unmixing is achieved through the application of a spectral mixture model. An alternative to this is to define relationships between a measure of the strength of class membership, which may be derived from some image classification routines and the pixel composition *(Foody and Cox 1994).* This paper defines a new method for direct classification and estimation of the sub-pixel land cover classes in addition to pure pixels.

2. PHILOSOPHY OF THE METHOD

The approach outlined in this paper is based on the premise that *classes of objects in which the transition from membership to non-membership is gradual rather than abrupt*, which intuitively correlates with the spatial distribution of the land cover classes. As land covers are imprecise in spatial distribution with reference to IFOV (Instaneous Field Of View) of the satellite sensors, fuzzy labels (Zadeh, 1973) provides a better framework of representation of class information. Generally, the more a pixel contains a cover class, greater is the proportion of spectral characteristics of that class in that pixel *(Wang, 1990).* As the mixture proportion changes from pixel to pixel, the spectral characteristics will also change. In fuzzy representation, for remote sensing image analysis, land cover classes are defined by fuzzy sets (Zadeh, 1965) where FEATURES are linguistic variables, image pixels are set elements and the membership grades attached to a pixel indicate the extent to which the pixel belong to a certain class/ classes.

As better resolution of images enhances the intrinsic heterogeneity (scene noise) of images, conventional classification techniques do not lead to better results *(Townshend, 1980).* So an "image understanding system" using subtle differences of multi - spectral responses in synergistic consideration has been adopted. It is characterised by *a priori* knowledge of the real world. In determining the *a priori* knowledge, the domain knowledge of land covers in multi-spectral perspective, expert's heuristics and training area informations are used.

3. METHODOLOGY

The land cover classes are first categorised in a hierarchical order (See Appendix A). Then the working of the understanding system proceed from top to bottom i.e., from general to particular type of cover.

The steps involved in the operation of the proposed understanding system are enumerated as follows:

Step1 Selection of appropriate data (based on sensor, band, temporal and spatial consideration).
Step2 Preprocessing operation (geo-referencing, inter-band registration, atmospheric correction etc).
Step3 Finding out values of the linguistic variables. (Rule-base decides the linguistic variables to be considered).
Step4 Selection of the threshold values corresponding to fuzzy labels (using training sets).
Step5 Conversion of linguistic variables and fuzzy labels into the "database of facts".
Step6 Sequential addressal of database of facts in order to infer land cover type using "RULE BASE".
Step7 Determination of category membership value using *possibilistic function* of AND operator.
Step8 Determination of "multi-category" (repeating steps 6 & 7 as many times as the rule-base permits).
Step9 Finding out of the hard classification (addressing multi-categories (of the same pixel) and using *possibilstic function* of OR operator).
Step10 Repeat (the steps 6,7,8 & 9) till the end of the database.

4. CASE STUDY

The present study is limited to the top level of the classification hierarchy as outlined in Appendix A. Land cover classes have been broadly classified into three classes i.e., water, land and vegetation. However, the basic principle of working will be the same throughout when the above methodology is extended to sub-classes of land cover. After preprocessing of satellite data, a few sets of training areas for each of the cover types are selected both from homogeneous and heterogeneous areas. For the present study, the Rule Base has selected the following LINGUISTIC VARIABLES : NDVI (Normalised Difference Vegetation Index), HUE * and TONE (red band). The domain knowledge available with these variables are given in Table1. Further the overlapping characteristics of the fuzzy labels make these variables suitable for the present study.

* Hue (FCC) is calculated by

$$\text{Hue, } H = \cos^{-1} \frac{(1/2) * [(IR-R) + (IR-G)]}{[(IR-R)2 + (IR-G)(R-G)]1/2} \quad \text{for } G \leq R$$

$$= 360^{\circ} - H \; ; \quad \text{for } G > R$$

where G, R and IR are respectively green, red and infra-red band reflectance values.

Table 1. *Domain Knowledge associated with Linguistic Variables and Fuzzy Labels.*

Fuzzy Labels / **Linguistic Variables**	Low	Medium	High
NDVI	Water	Soil	Vegetation
HUE	Soil	Water	Vegetation
(RED BAND) TONE	Vegetation	Soil	Water

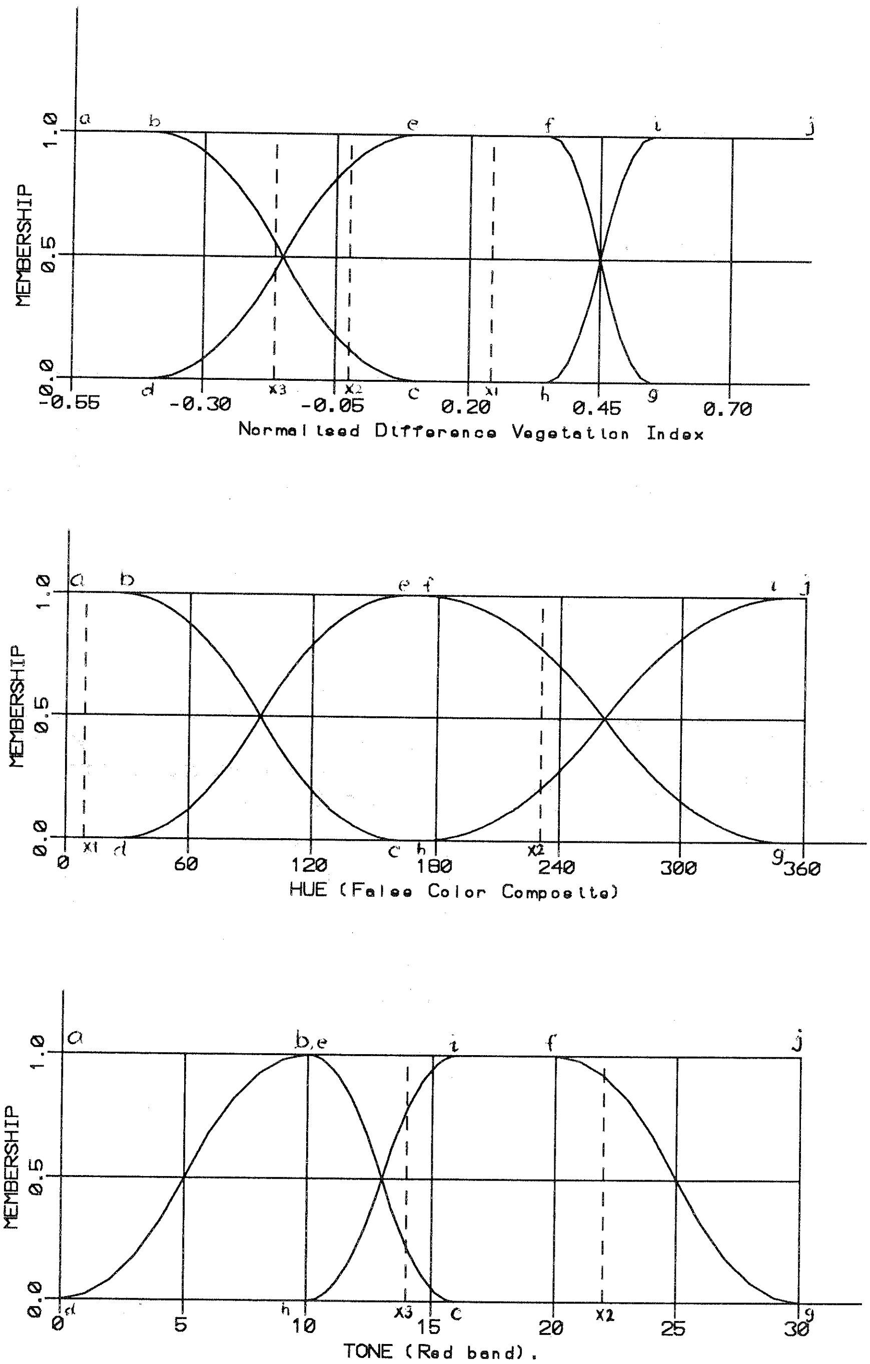
After calculating the desired linguistic variables (NDVI, HUE, TONE) using the relevant module at STEP 3, the threshold values of fuzzy labels and their transitional range from full membership to non-membership are found out at STEP 4. The three ranges of values which represents the experts' fuzzy labels low, medium and high alongwith their transition from low to medium and medium to high are shown in Figure 1. The desired threshold values used in the present study is given in Table 2.

Table 2. *Threshold Values selected for Linguistic Variables of the study area.*

Points	Linguistic Variables		
	NDVI	HUE	TONE
a	-0.55	000	00
b	-0.40	026	10
c	0.10	164	16
d	-0.40	026	00
e	0.10	164	10
f	0.35	172	20
g	0.55	352	30
h	0.35	172	10
i	0.55	352	16
j	0.85	360	30

Zadeh's S-curve *(Zadeh, 1975)* has been used as characteristic function for defining the transition zones from one fuzzy label to other, as it represents the labels properly from membership to non-membership. The choice of S-function is also supported by the fact that the visual perception (simulating experts' intuition of tone and hue) of human eye is bell-shaped curve *(Jain,1984)* and that the maximum likelihood classification technique which generally provides better classification accuracy also assumes that the probability density function is a bell-shaped surface *(Estes et.al.)*. Further, the bell-shaped curve is also equivalent to Zadeh's π (pie) function *(Zadeh, 1975)* which is again a combination of two S-functions as shown in Figure 2.

Thus *by correlating domain knowledge and fuzzy representation it can be concluded that the characteristic functions denoting the fuzzy labels represents the land cover classes and the overlapping zones represent the multi-category of land cover classes i.e., the mixed pixels. The membership grades of the fuzzy labels denote the extent to which the pixel belongs to a certain class.*



Fuzzy Labels: LOW - abc; MEDIUM - defg; HIGH - hij;

Figure 1: Characteristics functions of Fuzzy Labels for NDVI, HUE and TONE.

By STEPS 5,6,7 and 8, each image point is assigned its (single or multi) category land cover which is based on *"Principle of Convergence"* and *"Possibilistic Function of AND operator"*. The Possibilstic Function has been developed on the basis as suggested by *Dubois and Prade (1988)*. The details of the same are given below:

Let $X=\{x_1,x_2,\ldots,x_N\}$ be the set of values of N linguistic variables for a given pixel X. The possibilistic function of AND operator representing the possibility of X to belong to class C is

$$\pi(C_i,X)=\min\{\mu_{c_i}(x_k)\}$$

where k=1,2,.....,N and
$\mu_{c_i}(x_k)$ represents the possibility of belonging of the pixel, having attribute value x of the linguistic variable k, to the class C_i .

In STEP 9, the possibilitic function of OR operator representing the hard class, C of the mixed pixel X is

$$\pi(C,X)=\max\{\pi(C_i,X)\} \quad \text{when varying } C_i.$$

By performing STEP 10, the desired output i.e., the classified land cover image, is obtained through the understanding system.

5. RESULTS

As a result of domain knowledge, heuristics and thresholding through training samples and convergence of evidences, a *rule base* is prepared to infer pure and mixed pixels. Some of the rule base used in determining the component proportion of the mixed pixel are
defind as follows:

5.1 Rule Base

RULE #
IF NDVI is High
AND HUE is (in overlapping of) Low and Medium
AND TONE is High
THEN cover type is (mixture of) WATER and SOIL.

RULE #
IF NDVI is (in overlapping of) Medium and High
AND TONE is (in overlapping of) Low and Medium
THEN cover type is (mixture of) SOIL and VEGETA TION.

RULE#
IF NDVI is High AND HUE is (in overlapping of) Low and Medium
AND TONE is (in overlapping of) Low , Medium and High
THEN cover type is (mixture of) WATER , SOIL and VEGETATION.

RULE#
IF NDVI is Medium
AND HUE is (in overlapping of) Medium and High
AND TONE is (in overlapping of) Low , Medium and High
THEN cover type is (mixture of) WATER , SOIL and VEGETATION.

As the pure pixels of each class have distinct characteristics as defined in the domain knowledge, only NDVI and HUE is sufficient to satisfy the convergence in determining the cover type, whereas, mixed pixel gets identified and estimated using the overlapping of labels. The variables addressed by the rule-base are considered for the possibilistic calculation.

5.2 Illustrative Exapmples

EXAMPLE 1.
A sample, X1(Refer fig.1) which has NDVI and HUE values of 0.26 and 9.83 respectively represents fuzzy labels as Medium and Low. As both the labels represents the same land cover type i.e. soil, so by *"Convergence of Evidence"* principle, it can be inferred that the land cover type is SOIL.

In order to find the membership category, the membership values of fuzzy labels are found to be respectively 1.0 and 1.0 (refer Fig.1). By applying the Possibilstic function of AND operator, the membership value of the pixel as soil cover is found to be 1.0 i.e.,it is a pure pixel of SOIL.

EXAMPLE 2.
Sample, X2 (Refer fig.1) has NDVI and HUE values of -0.02 and 229.1 respectively. It is found that NDVI gives a fuzzy label of low and medium i.e., the sample is a mixed pixel of water and soil, whereas HUE gives a fuzzy label of Medium to High i.e., the sample contains both water and vegetation. As the labels represent different land cover types, so in order to resolve the ambiguity, the fuzzy variable TONE is further examined and the value is 22. The corresponding fuzzy label is Medium and High, thus indicating that the pixel as a mixture of soil & water. By applying *"Convergence of Evidence"* principle, it can be now inferred that the sample is a mixture of WATER and SOIL only, and that vegetation is excluded as it appears only in one case.

For determining the category membership of the pixel, different membership values for water are 0.12, 0.996 and 1.0 and for soil these are 0.88 and 1.0 from different linguistic variables. Using Possibilistic Function of AND operator, the membership value of water and soil are found to be 0.12 and 0.88. The hard class, using possibilistic OR operator, of the pixel is classified as SOIL.

EXAMPLE 3.
A sample, X3 (Refer fig.1) has NDVI and HUE values of -0.17 and 180 respectively. It is found that NDVI gives a fuzzy label of Low & Medium i.e., the sample is water & soil, whereas HUE gives a fuzzy label of Medium to High i.e., the sample contains both water and vegetation. In this case as the labels represent different land cover types, so in order to resolve the ambiguity, the fuzzy variable TONE is examined and has a value of 15. The fuzzy label Low & Medium assigns the pixel as a mixture of soil, water & vegetation. By applying " *Convergence of Evidence*" principle, it can be inferred that the sample is a mixture of all the three land cover types.

For determining the category membership of the pixel, the different membership values for water are 0.55, 0.95 and 0.67, for soil these are 0.45 and 1.0 and for vegetation 0.08 and 0.17. Using Possibilistic Function of AND operator, the membership value of water, soil and vegetation are found to be 0.55, 0.45 and 0.05 respectively. The hard class, using possibilistic OR operator, of the pixel is classified as WATER.

The summarised results of the examples as explained above is shown in Table 3.

6. CONCLUSION

The proposed method is less numerical intensive in comparison to standard and widely used classification methods like Bayesian Maximum Likelihood method and any other sub-pixel classification methods. This method can be utilised to develope a fully automated image understanding system. In doing so, it may be generalised to find the different types and numbers of constituent classes. In fact, it will be required to prepare a meta-level knowledge module to resolve the types of VARIABLES and their optimum combinations to be considered for different types of mixed pixel. However, to provide the exact category membership of the constituent classes, the membership functions of fuzzy labels may be defined on the basis of in-situ conditions as these may vary both spatially and temporally. The source of imprecision in this method lies in the manner in which fuzzy labels and fuzzy algorithms are applied to the formulation and solution of the problem.

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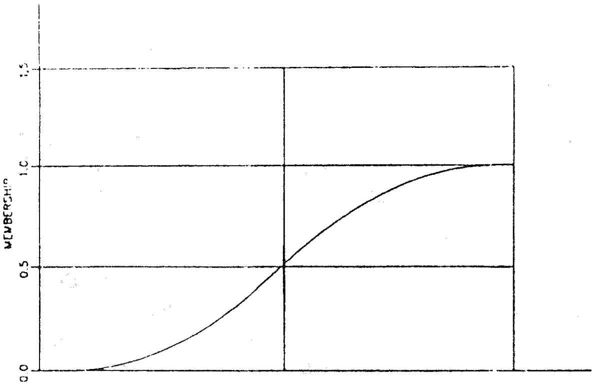

Figure 2(a). S function (after Zadeh,1975).

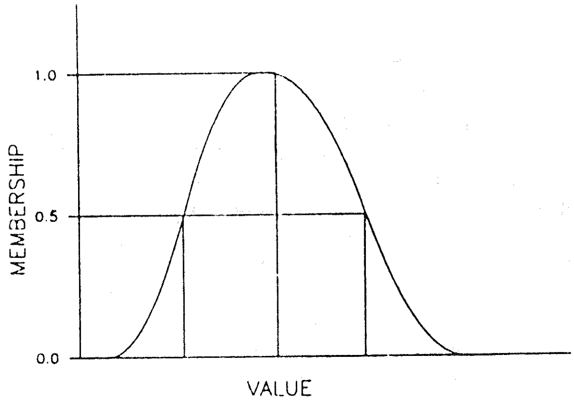

Figure 2(b): Π (bell shaped) function (after Zadeh,1975).

Table 3. *Summary of the results of examples*

SAMPLE NAME	Linguistic Variables			Fuzzy Labels for			INFERENCE	
	NDVI	HUE	TONE	NDVI	HUE	TONE	MIXED	HARD
X1	0.26	9.80	13	Medium(1.0)	Low(1.0)	Not Required	SOIL(1.0)	SOIL (Pure)
X2	-0.02	229.1	22	Low(0.12) Medium(0.88)	Medium(0.8) High(0.2)	Medium(1.0) High(1.0)	SOIL(0.88) WATER(0.12)	SOIL
X3	-0.17	180.0	14	Low(0.55) Medium(0.45)	Medium(0.996) High(0.004)	Low(0.22) Medium(1.0) High(0.78)	WATER(0.55) SOIL(0.45) VEGETATION (0.004)	WATER

APPENDIX-A

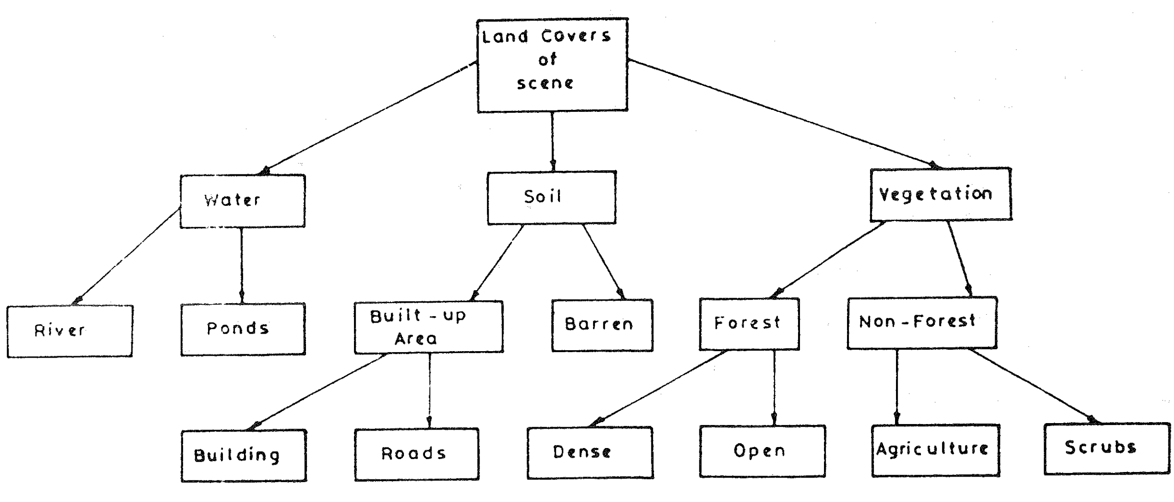

Fig. 3 Classification hierarchy of land covers