MAPPING OF TEA GARDENS FROM SATELLITE IMAGES -A FUZZY KNOWLEDGE-BASED IMAGE INTERPETATION SYSTEM.

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ABSTRACT

Detection and identification leading to interpretation and mapping of tea gardens from satellite images is the prerequisite for application of remote sensing technology to monitor and management of tea gardens. This paper discusses the development of a fuzzy knowledge-based image interpretation system for mapping of tea gardens from satellite images. It emulates the multi-stage, multi-feature and multi-iteration heuristics of an expert image analyst. Knowledge acquisitions for the system is achieved through spectral knowledge of land covers, domain knowledge and expert's heuristics. The knowledge base and feature attributes of the information classes are expressed by linguistic variables and fuzzy attributes. The inference mechanism is modeled on the basis of fuzzy logic. The system provides information of different types of land cover in each stage of its interpretation leading to mapping of tea gardens after the final stage. The mapping of tea gardens from IRS (Indian Remote Sensing Satellite) LISS (Linear Imaging Self Scanner) II geocoded images of an area in the district of Cacher in Assam (INDIA) has been carried out by the system developed. The results obtained from the working of the system in each stage of its operation as well as from the experimental study show that the developed system provides sufficiently accurate information in each stage of its interpretation. It has been found that the performance of the system is better than the minimum classification accuracy required i.e., 85% to justify the operational capability of the system. Thus it can be concluded that the developed system can be used reliably for mapping of tea gardens from satellite images.

1. INTRODUCTION

Tea is one of the most valuable natural resources of India. It commands a pivotal position in the nation's economy as it is one of the major forex earner for the country. Naturally there is always demand towards cost-effective techniques for continuous monitoring, assessment and management of tea gardens.

Remote sensing technology offers numerous advantages over traditional methods of conducting agricultural resource survey and management (Myers, 1983). However, detection and identification leading to interpretation and mapping of the tea gardens from satellite images is the prerequisite for application of remote sensing technology to monitor and management of tea gardens. The mapping of tea gardens from satellite data can be carried out either by photointerpretation or by quantitative analysis.

Ghosh et. al (1992) interpreted IRS LISS II images visually to delineate tea gardens along with other land covers of a region in Barak Valley of Assam, India. Pal et al (1993) also applied visual interpretation technique to delineate and assess the condition of tea gardens from satellite images.

However, analysis by photointerpretation method has some serious drawbacks. One of the major limitations lies in its inconsistency in output, to be more specific, in the segmentation process. This is due to inherent fuzziness of expert's cognition and interpretation process as well as that of the satellite data. Moreover, this method can assimilate only a limited number of distinct brightness levels and has limited multi-spectral analysis capability.

The advances in computer technology have opened the vista for analysing satellite data using computational methods resulting in consistent output. It has capability to differentiate the full dynamic range of brightness values and also to analyse the whole range of mutispectral data. It also provides accurate quantitative measure. But approaches using crisp mathematical models for interpretation of satellite data can neither provide output comparable to that as given by an expert image analyst nor can it simulate the complex visual image interpretation process.

However, the framework of knowledge based (KB) system does provide powerful and flexible methodologies to analyse the domain-specific knowledge and heuristics of visual image interpretation. There are many KB systems developed for satellite image interpretation by many researchers [Goldberg et al. (1985), Civco (1989), Blonda et al (1991) etc.]. It is found that nearly all the developers attempt to follow photointerpretation process without taking care of the inherent fuzziness of analyst's cognition and reasoning processes and that of the satellite data. The approaches towards generalisation of some systems are also primitive.

Ghosh (1996a) adopted a fuzzy knowledge based approach for interpretation of land cover. Segmentation and classification of pixels were done simultaneously by addressing the Linguistic variables in their fuzzy labels. But the parameterizations of the characteristic function were carried out without taking care of the uncertainty associated with it and inference mechanism was crude.

The present paper discusses the development of an automated image interpretation system that follows a similar approach as adopted by Ghosh (1996a) but incorporates some new features to make it more logical and accurate. The proposed system is meant for mapping of the tea-gardens form satellite images.

2. THE PROPOSED SYSTEM

The broad objective of the proposed work is to develop an image interpretation system for mapping of tea gardens from satellite images emulating an expert image analyst. Experts, generally, use linguistic variables and their fuzzy labels to address facts and the domain knowledge of information classes. The reasoning for interpretation is also carried out by fuzzy inferencing (Zadeh, 1973). Thus, a fuzzy logic system has the capability to satisfy the objective of this work. The schematic representation of the proposed system of image interpretation is shown in Figure 1.

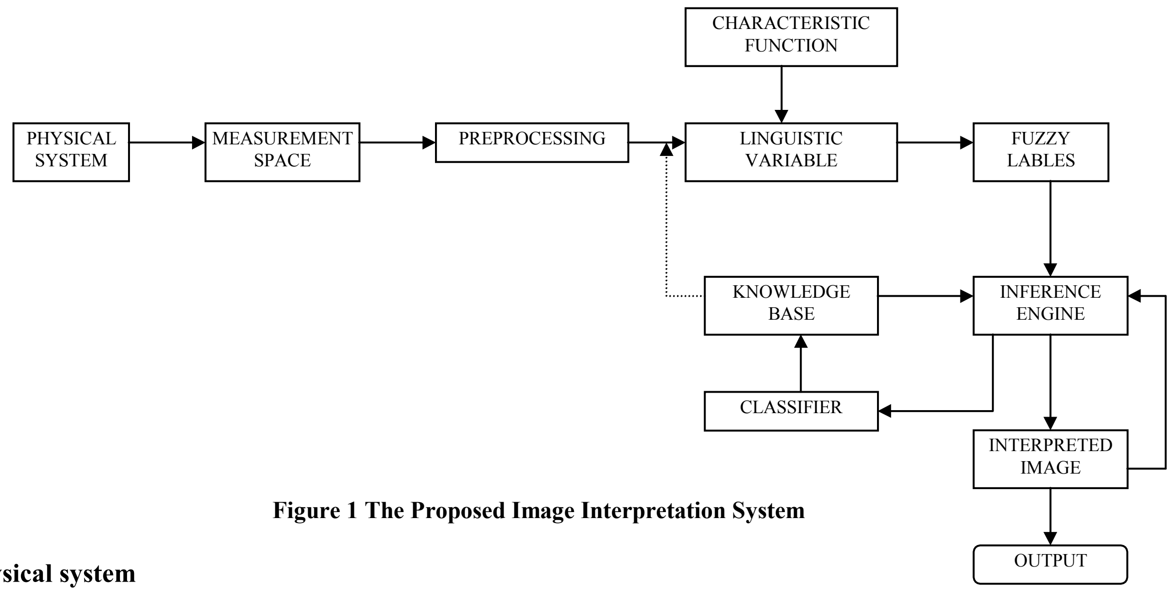

Figure 1 The Proposed Image Interpretation System

2.1 Physical system

The land covers within the study area represents the physical system module for the proposed system

2.2 Measurement space

Geocoded satellite data that represents the physical system module numerically, by spectral measurements at different bands, defines the measurement space module of the system.

2. 3 Preprocessing

The system is developed for interpreting geocoded satellite data. By this, it pre-supposes that the data to be interpreted is free from instrumentation error and geometric distortion. Thus the preprocessing module of the system is developed to take care errors due to atmospheric effect by dark object subtraction technique (Chavez, 1988).

2. 4 Characteristic Functions

In order to address the linguistic variables in terms of their fuzzy labels, the system using characteristic functions fuzzifies the input features. For Stage I and Stage II, standard S-function (Zadeh, 1975) or an inverse of it is used to define the characteristic functions. The parameterizations of these are carried out by Modified Fuzzy Threshold Technique (Ghosh, 1996b) where entropy, as a measure of uncertainty, is used as a criteria to find the threshold parameters. For Stage III and Stage IV, the threshold parameters are found by amplitude thresholding.

2. 5 Classifier

The basic philosophy adopted in designing the classifier is to divide the variability factors present in a scene into categories, which are related to the information desired and those that are not. The expert analyst's heuristics and domain knowledge about the land covers' implicit hierarchical structure has been primarily utilized for framing the classifier by Manual Design Procedure (Swain & Hauska, 1977). An expert analyst generally adopts a multi-stage classification scheme for interpretation of a satellite image involving multi-feature at each of classification. Thus, a binary decision tree classifier is designed for mapping of tea gardens from satellite images as shown in figure 2.

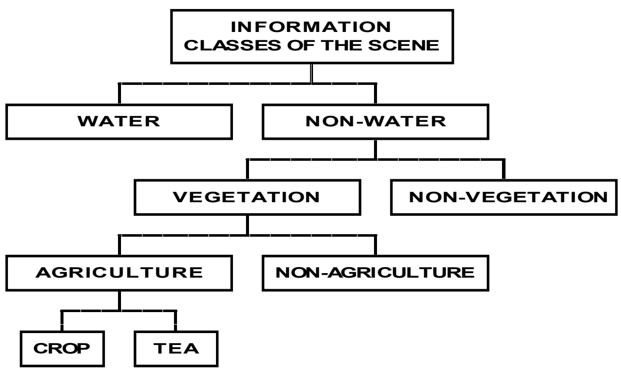

Figure 2 Binary Decision Tree Classifier

2. 6 Knowledge Base

The knowledge base consists of facts and principles accumulated from the spectral and spatial domain and from training data. It also contains most importantly the heuristics of satellite image interpreter. From the available features, subsets of features compatible to the stages of the decision tree classifier are decided by using hierarchical search. The domain knowledge in terms of linguistic variables and their fuzzy labels and parameters of the characteristic functions at different stages of the decision tree classifier used in the system is given in a summarized form in Table 1.

2. 7 Inference mechanism

The inference mechanism of the system involves composition rules of atomic fuzzy propositions. Suppose F and G is two fuzzy subsets of the universes U and V respectively. Let us consider, two atomic fuzzy propositions X is **F** and Y is **G** which can also be represented by the possibility distributions π_x and π_y respectively, where $\pi_x = \mathbf{F}$ and $\pi_y = \mathbf{G}$. Then according to Zadeh (1979, 1981), the composition of the propositions X is **F** and Y is **G** can be viewed as a particularization of the possibility distribution π_x by the possibility distribution π_y. In order to evaluate the particularization due to compound fuzzy proposition, the translation rules of fuzzy calculus developed by Zadeh (1979, 1981) have been used in the proposed system.

3. WORKING OF THE SYSTEM

The multi-stage classifier involving multi-features is used for inferencing in the system for image interpretation emulating an expert image analyst. The working of the proposed image interpretation system thus proceeds from top to bottom of the classifier i.e., from general to a particular type of land cover class. Before any classification is carried out, the linguistic variables of all the pixels of the preprocessed image are calculated and are stored in files in terms of their fuzzy labels. Separate files are maintained for different fuzzy labels of any linguistic variable. The inference is started from the top stage of the decision tree classifier and continued till the final stage

Table 1 Domain knowledge in terms of Linguistic variables, Fuzzy Labels and Threshold parameters at different stages of the interpretation.

STAGES	Cover Class	Linguistic Variables	Fuzzy Labels	Parameters
I	Water vs Non-water	(i) Band ratio (Band 4/ Band 3) (ii)Tone(Band 4)	Low & High Dark & Light	0.4, 0.9, 1.40 9, 14, 19
II	Vegetation vs Non-vegetation	(i) NDVI (ii) Saturation (FCC)	High & Low High & Low	0.35, 0.50, 0.65 0.3, 0.425, 0.55
III	Agriculture vs Non-agriculture	Contrast	Fine & Coarse	1.0*
IV	Crop vs Tea	(i)Tone(Band 3) (ii)Tone(Band 4)	Light & Dark Light & Dark	8* 45*

* Crisp categorisation.

simulating the use of "elimination keys" in visual image interpretation. Interpretation of the full image at each stage of the classifier is first completed before proceeding to the next step. The interpretation of the succeeding stage involves the output of the preceding stages. This process is similar to sieving operation where further analysis of the data is carried out only for those that satisfy the requirements of the previous stage. The interpretation process lies in addressing the appropriate rules (depending on the stage of the classifier) and to infer the possible information classes of the sample by using fuzzy rules of inference i.e., the Conditional conjunction rule and the Conjunction composition rule and to obtain a crisp output defuzzification is carried out by using the Disjunction composition rule.

Subsequently, at the first stage, water cover is interpreted against non-water land cover. At Stage II, the non-water category found at Stage I is interpreted to separate vegetative areas from non-vegetative areas. At Stage III, the vegetation category found at Stage II is further interpreted to separate out agricultural type vegetation from non-agricultural type vegetation. At Stage IV i.e., final stage, the agricultural type vegetation is interpreted to separate out crop from tea, leading to mapping of tea gardens from satellite images. Thus, each stage of interpretation, the system provides outputs that are useful sources of land cover information.

4. PERFORMANCE OF THE SYSTEM

The evaluation of the system for each stage of interpretation is experimented for actual data of the study area as well as that of the system for a synthetic image of reference data over and above the sample study of a sub-scene of the area.

4.1 Experimental Results

The sub-pixel membership values of water cover interpreted by the proposed interpretation system at the first stage are compared to those of the expected values. An excellent correlation [0.9504] is found between the two while the accuracy for hard classification is found to be 96 percent (Ghosh, 2000a*)*. The correlation between the estimated values of the different types of vegetative covers, interpreted at Stage II, in association with different types of non-vegetation compared to those of the expected values and are found to be more than 0.95 and hard classification shows more than 95 percent accuracy on an average (Ghosh, 2000b). The overall accuracy of spatial analysis of vegetation types into agricultural vegetation and non-agricultural vegetation is 86.30 percent. The overall accuracy analysis to classify agricultural vegetation into tea and crop is 94.87 percent (Ghosh, 1996b).

4.2 Performance Evaluation

To carry out the performance evaluation of the developed system, 256 reference samples of nine broad categories of the land covers present in the study scene are collected from VDU near the training fields and supported by ground reconnaissance. They are arranged in rows and columns to form an image of 16 X 16 in a way as the study scene appears. Now the interpretation of the image is carried out by the developed system and classification by the minimum distance to means classifier after using the same set of training samples for both. The output of the proposed system of interpretation and that of statistical classification algorithms are compared with respect to the reference data and resulted in the error matrices (Ghosh, 1996b). The commission of tea to non-agricultural vegetation is more than expected in the output of the developed system for image interpretation. This is because of artificial arrangement of samples in the test image. The non-uniformity in the transition from tea to other classes in the test image results from coarse spatial contrast and thus, commission to non-agricultural vegetation. It is found that the overall classification accuracy of the proposed system is about 88 percent and that statistical minimum distance to means classifier is about 77 percent. Thus, the proposed system gives much better result than minimum distance to means algorithm. It is expected that the commission of tea to non-agricultural vegetation category will be much less in case original scene and thus will result in further improvement in overall accuracy by the system

4.3. Sample study

A sub-scene consists of 165 rows and having 165 pixels in each row is taken to evaluate the performance of the proposed system on satellite image. The FCC of IRS LISS II image of the sub-scene is shown in Plate 1. The mapping of tea garden from satellite image by the proposed image interpretation system is shown in Plate 2. The output of the sub-scene, classified by the minimum distance to means classification algorithm, is shown in Plate 3.

The results of histogram analysis of the land cover classes are given in Table 4. However, a comparison between the two methods has been carried out. It is found that the numbers of pixels in the pure class of water, interpreted by proposed system of image interpretation is consistent with the number of pixels under water by the minimum distance to means classifier. The proposed system also provides additional information regarding the number of pixels under graded category. It can be noted that the sub-pixels (having graded membership more than 0.5 and less than 1.0) are interpreted by the system as water which has been mostly classified as non-water by minimum distance classifier. This is a significant enhancement regarding the information content in the output of the proposed system of image interpretation. The effect of this enhancement of information content can be visualised more prominently by considering the Stage I output of the proposed system of image interpretation and that from minimum distance to mean classifier (Ghosh, 2000a).

Table 4 Comparison of the Results of outputs of the sub-scene

Land Cover Types	Proposed System of Image Interpretation			Minimum Distance to Means Classifier	
	Number of Pixels		Area (Sq. Km)	Number of Pixels	Area (Sq. Km)
	Pure	Hard class			
Wat	224	337	0.468	236	0.31
NW	26,665	26,834	35.31	26,989	35.47
Veg	19,191	23,985	30.99	19,143	25.15
NV	1,114	2,903	4.31	7,846	10.31
NA	5,152		6.77	3,840	5.05
Crop	1,546		2.05	1,117	1.47
Tea	12,113		15.92	14,186	18.64

Legend: WAT - Water; NV - non-water non-vegetation; NA - non-agricultural Vegetation; CD - classified data; RD - reference data.

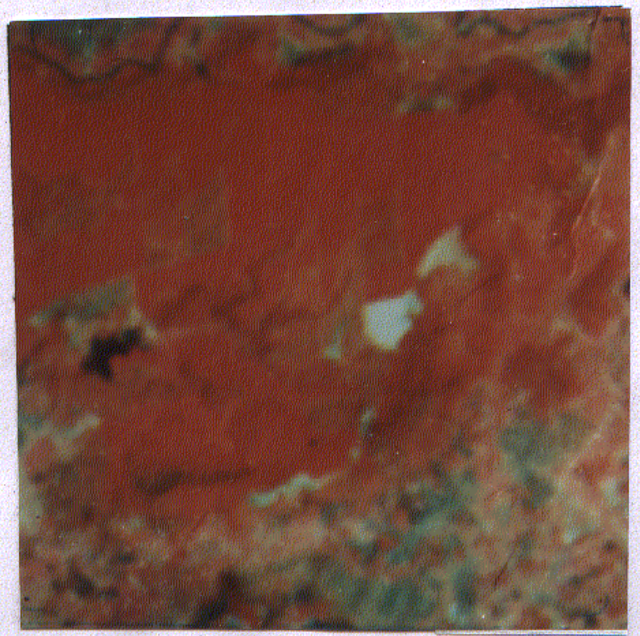

Plate 1 FCC of the sub-scene

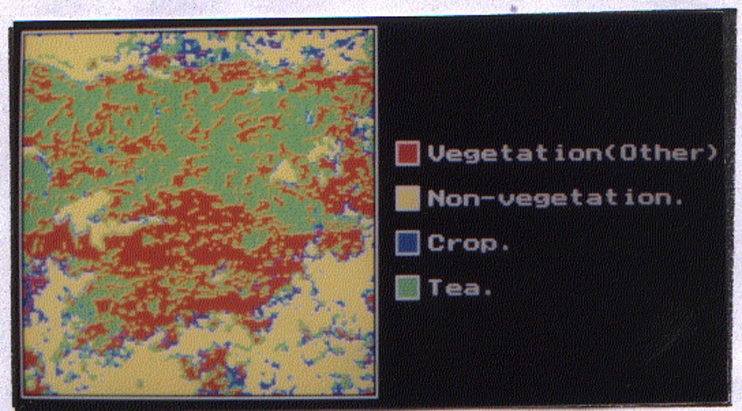

Plate 2 Tea-garden of the sub-scene interpreted by the proposed system

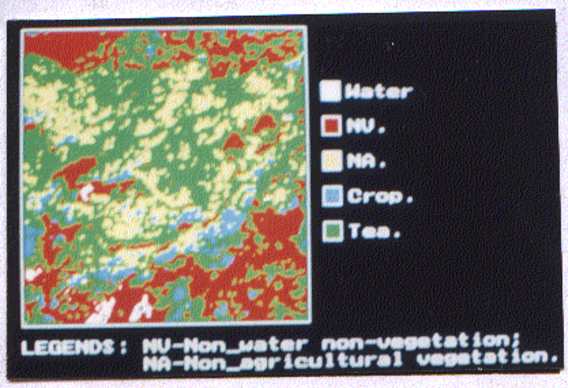

Plate 3 Classification of the sub-scene by Minimum Distance to Means Classifier

The linear water body at the top of the sub-scene is not present at all in the output of the minimum distance classifier (Plate 3). Whereas, the presence of the linear water body at the top of the image can be authenticated from FCC (Plate 1). The FCC also depicts that the considered linear water body is not as prominent as pure water bodies present in other part of the image. Thus, sub-pixel analysis by the proposed system provides some vital information regarding the information class, which is not possible through standard statistical methods. Other important factor is that the graded water bodies also comes into consideration for calculation of area under water in case of proposed image interpretation system but not in minimum distance to mean classifier and thus, improving the accuracy of area estimation by the proposed system.

In classification of vegetation, there is a marginal difference (about 48 pixels i.e., about 0.2%) between the number of pixels classified by the minimum distance to means classifier and that interpreted by the system as pure class but there is a significant difference (4,482 pixels i.e., about 25%) with the number interpreted as hard class. This discrepancy is transmitted to non-water non-vegetation category. Interestingly, the difference (4,943 pixels) between the number of non-vegetation under hard class interpreted by the system and that by minimum distance to means classifier is more or less same as the difference (4,842 pixels) between the number of vegetation under hard class and that by minimum distance to mean classifier. This clearly signifies that most of the sub-pixel vegetation of hard class has been classified as non-vegetation by the minimum distance to means classifier. Also, the non-vegetation hard class pixels of the system are mostly interpreted by the minimum distance to means classifier also as non-vegetation.

Thus, it can be concluded that enhancement in classified information is depicted in the classification of the proposed system of image interpretation by accounting sub-pixel analysis. The sub-pixel analysis by the proposed system provides information regarding the pure information classes, the pixels under graded category, the extent of gradation, detail information about areas under different categories. In case of interpretation of different vegetation types, it is found that there is a discrepancy in the numbers of pixels as interpreted by the system and that by minimum distance to means classifier.

The spectral similarity between non-agricultural vegetation (specifically, scrub vegetation a component of non-agricultural vegetation) and tea may be the cause of large commission of non-agricultural vegetation to tea class in the classification of the minimum distance to means classifier. On the other hand, the inter mingling of the information classes causes coarser spatial texture at the boundary of tea gardens may result in some omission error in tea category to non-agricultural vegetation in the classification of the proposed interpretation system. These results in significant difference in the classification of the two approaches. However, by comparing the classification of the interpretation system (Plate 2) with the FCC of the sub-scene (Plate 1), it is found that the mapping of tea gardens of the sub-scene is done quite satisfactorily by the proposed system.

5. DISCUSSION

It is observed that the adopted model performs excellently in calculating mixed pixel contents. Thus, sub-pixel analysis of water and vegetation from satellite images can be done reliably by the proposed method. From the experimental result, it can be assured that the discrepancy between the expected and the estimated values of the partial membership in information classes will be maximum 15 percent i.e., estimated values are within 15 percent higher or lower than expected values. The mis-classification, if any, in finding the hard classes will arise in pixels having 40 to 60 percent component cover classes. The experimental results show that to estimate area under different land cover the proposed method will give good result. The model also performs well to classify agricultural vegetation from non-agricultural vegetation and that crop from tea. From the sample study, it can be concluded that the proposed method is a viable system for mapping of tea gardens from satellite images.

6. CONCLUSION

In this research work, a novel method has been studied for developing a humanist system for automated mapping of tea gardens from satellite image. Integration of domain knowledge and photo interpreters' heuristics with the techniques of image processing, artificial intelligence and pattern recognition have been tried. The results show that the adopted method can be applied for mapping of tea gardens of the study area from the considered data. The system shows excellent performance in sub-pixel classification of land covers. It provides a huge enhancement of land cover information in comparison to the existing classification schemes. The sub-pixel interpretation of land covers also improves the accuracy of estimation of area under different land covers. However, the ultimate aim of developing a humanistic image interpretation system is to have a viable and versatile alternative to expert image analysts who are rare and not readily available. Despite the progress has been achieved in this work, the developed system is too primitive to replace an expert photointerpreter

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