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EFFICIENT TECHNIQUE FOR THE CLASSIFICATION OF SATELLITE IMAGES USING FUZZY RULE CLASSIFIER

[1]S.PRABHU, [2]DR.D.TENSING

[1]Research Scholar,
Associate Professor, Department of Computer Science and Engineering, Kalaivani college of Technology
Coimbatore, Tamil Nadu, India
[2]Principal A.S.L. Pauls College of Engineering and Technology
[1]E-mail: amsprabhu.phd@gmail.com, [2] dtensing@rediffmail.com

ABSTRACT

The proposed technique is used classify the satellite image into barren land, vegetation area, building area and road area. Initially, the satellite image is pre-processed and then is then segmented to have segments of barren land, vegetation area, building area and road area. The featuresof the segmented area are extracted and then final classification is carried out using fuzzy rule classifier. In the result section, classified output satellite images obtained are shown and proposed technique is evaluated by means of accuracy parameter. The accuracy obtained is high having an average of 92.56%. We also compare to normal graph cut and from the results, it is proved that our proposed technique using modified graph cut have obtained better results.

Keywords: *Remote Sensing, Multispectral Satellite Image, Clustering, Classification, Modified Graph Cut Segmentation, Fuzzy Classifier*.

1. INTRODUCTION

Remote sensing is a versatile tool for exploring the Earth and it involves the application of instruments or sensors to “capture” the spectral and spatial relations of objects and materials discernible at a distance. Aerial and satellite images, known as remotely sensed images, permit accurate mapping of land cover and make landscape features understandable on regional, continental, and even global scales. It has been extensively made use of for the monitoring of the earth surface to decide on the changes in land use and land cover [1]. It can also be used in creation of mapping products for military and civil applications, evaluation of environmental damage, monitoring of land use, radiation monitoring, urban planning, growth regulation, soil assessment and crop yield appraisal [11]. It is also used for mapping and classification of land cover features namely vegetation, soil, water and forests and acts as a substitute for traditional methods that perform land cover classification using expensive and time-intensive field surveys [12].In recent years, research has progressed in computer vision methods applied to remotely sensed images such as segmentation, object oriented and knowledge-based methods for classification of high-resolution imagery [25].

This object-oriented representation was mainly based on the image semantics and the explicit knowledge of the human expert. In order to classify each element of the image into the appropriate class, the knowledge based expert system represented the definitions of the classes through rules and heuristics, which an expert explicitly declares and develops within the system [27]. As a result, more complex methods for image classification have been implemented and many more image features can be used for the classification step [28]. Very recently a new methodology called Object Oriented Image Analysis was introduced, integrating low-level, knowledge-free segmentation with high-level, knowledge-based fuzzy classification methods [29].The several real world applications of remote-sensing data include: (i) monitoring forest tree species; (ii) determining the status of a growing crop; (iii) defining urban patterns; (iv) delineating the extent of flooding; (v) recognizing rock types and (vi) pinpointing areas of deforestation [1].

Satellite image classification includes mainly two steps [30]: (a) Segmentation step, and (b) Classification step. The chief objective of image segmentation is to partition the image into parts of strong correlation with objects or areas of the real world contained in the image [2]. Image segmentation is typically carried out as a pre-processing step for some land-cover and land-use classification systems [3, 4, 5]. Image classification

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can be defined as processing techniques that apply quantitative methods to the values in a digital yield or remotely sensed scene to group pixels with identical digital number values into feature classes or categories. The categorized data thus obtained may then be employed to create thematic maps of the land cover present in an image [6, 7].

Classification of multispectral images is one of the demanding techniques in the quantitative interpretation of remotely sensed images. Remotely sensed images typically engross a pixel (picture element) having its characteristics recorded over several spectral channels [8]. The output from a multispectral classification system is a thematic map in which each pixel in the original imagery has been categorized into one of numerous spectral classes [9]. The key steps of image classification includes (i) Determining a appropriate classification system, (ii) selecting training samples, (iii) image preprocessing, (iv) extracting features, (v) selecting fitting classification approaches, (vi) post-classification processing, and (vii) accuracy assessment. The user's need, scale of the study area, economic condition, and analyst's skills are significant factors that influence the selection of remotely sensed data, the design of the classification procedure, and the quality of the classification results. In general, the multispectral data utilized to perform the classification and, indeed, the spectral patterns present within the data for each pixel are used as the numerical basis for categorization [10].

For classifying the satellite images, lot of classification algorithms presented in data mining and Artificial Intelligence have been extensively used. In spite of all the advantages, classification of remotely-sensed imagery is a challenging subject because of the complexity of landscapes and the spatial and spectral resolution of the images being employed.Multispectral remotely sensed images comprise information collected over a large range of variation on frequencies and these frequencies vary over diverse regions [13, 14, 15]. Hence, proficient scheme capable of effectively deploying the spectral and spatial information present in the remote sensing data can improve the classification performance appreciably, compared to the conventional non-contextual information-based methods [16]. Generally, a classification system creates a classification map of the identifiable or meaningful features or classes of land cover types in a scene [17, 18].

Image classification can be viewed as a joint venture of both image processing and classification techniques [19]. Several methods of image classification exist and a number of fields, apart from remote sensing like image analysis and pattern recognition, make use of a significant concept, classification. Moreover, the selection of the appropriate classification technique to be employed can have a considerable upshot on the results of whether the classification is used as an ultimate product or as one of the numerous analytical procedures applied for deriving information from an image for additional analyses [19]. In recent times, various studies have applied artificial intelligence techniques as substitutes to remotely-sensed image classification applications [20]. In addition, diverse ensemble classification methods have been proposed to significantly improve classification accuracy [21]. A considerable number of research efforts have been made to take advantage of neighbouring pixel information [13, 23, 24] and applied for the classification of remotely sensed data.

In the proposed technique, the input image is pre-processed using Gaussian filtering and conversion of RGB to Lab colour space image so that the image is befittingly for segmentation. Subsequently, image is segmentedby modified graph cut algorithm for barren land and intensity constraint for other segmentation. Features such as perimeter, area, entropy and information gain are extracted from the segmented areas. For classification of the image into various segments such as barren land, building area, vegetation and roads, we make use of fuzzy rule classifier.

The rest of the paper is organized as follows: A briefreview of researches related to the proposed technique ispresented in section 2. The proposedtechnique is presented inSection 3. The detailed experimental results and discussions are given in Section 4. The conclusions aresummed up in Section 5.

2. REVIEW OF LITERATURE SURVEY

Literature presents a handful of researches for classification of satellite images and has been a hot topic due to its significant applications. Here, we present a brief review of some of the techniques presented in the literature for classifying the satellite images. Chu He et al. [31] presented a method for unsupervised urban area extraction from synthetic aperture radar (SAR) images based on the ffmax algorithm proposed by C. Gouinaud specially for acquiring urban areas in SPOT imagery. According to the statistical characteristics of urban areas, an adaptive and iterative method based on the

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low-level extraction given by the ffmax algorithm using a large window was proposed. Experimental results on real SAR images showed that the proposed automatic method worked quickly and could preserve the borders of urban areas as well as avoid the disturbance of other classes and the extractions of urban areas were reliable and precise.

Gidudu Anthony et al. [32] proposed a 'committee' of classifiers which was used to determine the final classification output. Two of the key components of an ensemble system were that there should be diversity among the classifiers and that there should be a mechanism through which the results were combined. In the paper, the members of the ensemble system included Linear SVM, Gaussian (Radial Basis Function) SVM and Quadratic SVM. The final output was determined through a simple majority vote of the individual classifiers. From the results obtained it was observed that the final derived map generated by an ensemble system can potentially improve on the results derived from the individual classifiers making up the ensemble system. The ensemble system classification accuracy was, in this case, better than the linear and quadratic SVM result. It was however less than that of the RBF SVM.D

Chutiaand DK Bhattacharyya [33] presented an Object oriented feature extraction approach in order to classify the linear features like drainage, roads etc. from high resolution Indian satellite imageries. It started with the multiresolution segmentations of image objects for optimal separation and representation of image regions or objects. Fuzzy membership functions were defined for a selected set of image object parameters such as mean, ratio, shape index, area etc. for representation of required image objects. Experiment was carried out for both panchromatic (CARTOSAT-I) and multispectral (IRSP6 LISS IV) Indian satellite imageries. Experimental results showed that the extraction of linear features was achieved in a satisfactory level through proper segmentation and appropriate definition and representation of key parameters of image objects.

Alberto Fernándezaet al.[34] aimed to improve the performance of fuzzyrule based classification systems on imbalanced domains, increasing the granularity of the fuzzy partitions on the boundary areas between the classes, in order to obtain a better separability. They proposed the use of a hierarchical fuzzy-rule based classification system, which is based on the refinement of a simple linguistic fuzzy model by means of the extension of the structure of the knowledge base in a hierarchical way and the use of a genetic rule selection process in order to get a compact and accurate model. The good performance was shown by the approach through an extensive experimental study carried out over a large collection of imbalanced data-sets.

Jan Knorn et al. [35] tested the classification of Landsat images based on the information in the overlapping areas of neighboring scenes. The basic idea was to classify one Landsat scene first where good ground truth data was available, and then to classify the neighboring Landsat scene using the land cover classification of the first scene in the overlap area as training data. They tested chain classification for a forest/non-forest classification in the Carpathian Mountains on one horizontal chain of six Landsat scenes, and two vertical chains of two Landsat scenes each. They collected extensive training data from Quickbird imagery for classifying radiometrically uncorrected data with Support Vector Machines (SVMs). The SVMs classified 8 scenes with overall accuracies between 92.1% and 98.9% (average of 96.3%). Accuracy loss when automatically classifying neighboring scenes with chain classification was 1.9% on average. Chain classification thus performed well, but they noted that chain classification could only be applied when land cover classes were well represented in the overlap area of neighboring Landsat scenes. As long as this constraint was met though, chain classification was a powerful approach for large area land cover classifications, especially in areas of varying training data availability.

ArijitLaha and J. Das [36] designed a fuzzy rule based classifier. The performance of the classifier for multispectral satellite image classification was improved using Dempster- Shafer theory of evidence that exploits information of the neighboring pixels. The classifiers were tested rigorously with two known images and they obtained good results.

Yousefiet al.[37] presented a fuzzy based method for 3d modeling of tall buildings and towers using a single satellite image. Firstly,vegetations based on green layer of image and amount of gradient and image intensity were filtered out and afterwards, buildings were segmented. In the next step, according to the fuzzy membership functions obtained from structural context, the roof of each building was segmented from building walls. To make a 3d model of buildings, the side of building walls that present their height was manually selected by the human operator and other buildings were modeled by the set angle. To benchmark the

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algorithm it was applied to some images from Sydney, Australia and the experimental result showed that the method could efficiently model the buildings which had at least two sides obvious in the satellite image.

Akif Mohammed Al Fugaraet al.[26] studied the land cover types in the Klang valley, Malaysia and analyzed to compare classification accuracy between the pixel-based and the object-oriented image classification approaches. Landsat 7 ETM+ with six spectral bands was used for the land cover classification. In the pixel-based image classification, supervised classification was performed using the maximum likelihood classifier. On the other hand, the object-oriented image classification was performed using the combination of object segmentation using fuzzy dimension techniques. Fuzzy dimension functions were devised to classify the segmented image objects. The classification results showed that the object-oriented cum fuzzy logic approach was superior to that of the pixel-based supervised classification.

3. PROPOSED TECHNIQUE FOR CLASSIFICATION OF MULTISPECTRAL SATELLITE IMAGES USING MODIFIED GRAPH CUT ALGORITHM

The proposed technique for classification of multispectral satellite images is discussed in this section. In the technique, the input image is pre-processed using Gaussian filtering and conversion of RGB to Lab colour space image so that the image is befittingly for segmentation. Subsequently, image is segmentedby modified graph cut algorithm and features are extracted from the segmented areas. For classification of the image into various segments such as barren land, building area, vegetation and roads, we make use of fuzzy rule classifier. The block diagram of the proposed approach is given in figure 1.

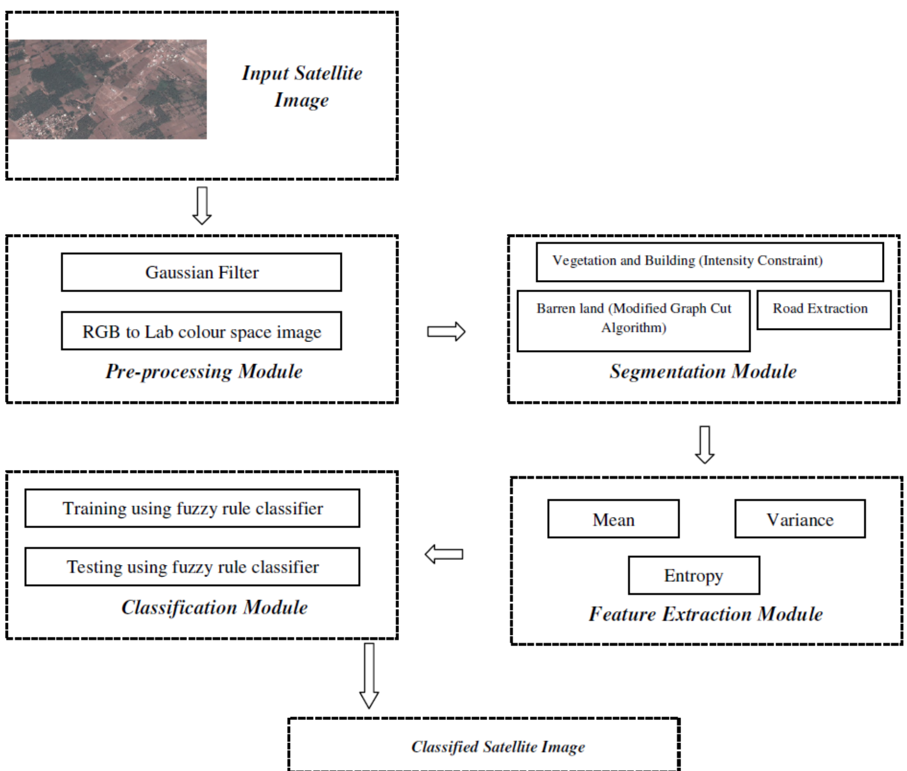

Figure1: Block Diagram Of The Proposed Approach

3.1 Pre-Processing Module

The input satellite image is pre-processing so that the image gets transformed suitably for the further processing including segmentation and feature extraction. The pre-processing employed is a two step methodology involving Gaussian filtering and conversion the image from the RGB model to Lab colour space Image.

A. Gaussian filter: Gaussian filter is a linear filter which is generally employed to filter out the noise and smoothen the image. It is an example of window filter and is named after famous scientist

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Carl Gauss.Gaussian distribution which is a probability theory function and also called bell-function because of its shapeis used to calculate the weighted average. Gaussianfilter can be used for both one-dimensional and two dimensional cases. The cut-off frequency of the filter can be taken as the ratio between the sample rateF_s and the standard deviation σ .

$$f_c = \frac{f_s}{\sigma}$$

The 1D Gaussian filter is given by the equation:

The impulse response of the 1D Gaussian Filter is given by:

$$g(x) = \frac{1}{\sqrt{2\Pi}\sigma} e^{\frac{-\sigma^2 u^2}{2}}$$

In two dimensional images, the distribution creates a surface whose contours are represented as concentric circles having Gaussian distribution from centre point. Distributed values are used to build a convolution matrix which is applied to original image. Weighted average of every pixel's neighbourhoods is taken and set as a new value of the pixel. Original value of pixels gets highest weight and as the distance of neighbouring pixel increases they receive smaller weights.Hence, the input image is Gaussian filtered in the pre-processing stepwhich results in an image having reduced noise and also results in obtaining an image fit for further processing. Gaussian filtering also improves the image quality.

B. Conversion of RGB to Lab colour space Image:A Lab color space is a color-opponent space with dimension L for lightness and 'a' and 'b' for the color-opponent dimensions, based on nonlinearly compressed CIE XYZ color space coordinates. Different from the RGB and CMYK color models, Lab color is developed to approximate the human vision. It aims for perceptual uniformity, and its L component relatively corresponds to human perception of lightness. It is therefore used to make accurate color balance corrections by changing the output curves in the 'a' and 'b' components, or to regulate the lightness contrast using the L component. In RGB or CMYK spaces, which model the output of physical devices instead of the human visual perception, these changes are done with the aid of the corresponding blend modes in the editing application.

3.2 Segmentation

The pre-processed satellite image is subsequently segmented to have segments of barren land, vegetation, building area and road. Segments of building and vegetation are found out using intensity constraint, barren land by modified graph cut segmentation method and road by segmentation technique.

a) Segmentation of building and vegetation areas

The building and vegetation areas from the satellite image are segmented by the use of the intensity constraint. The RGB image is converted to greyscale image where the image is composed exclusively of shades of grey, varying from black to white based on intensity value.A greyscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Greyscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colours, black, and white. Greyscale images have many shades of grey in between and are also called monochromatic, denoting the presence of only one colour. Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum.

The greyscale image is then contrast adjusted the image is enriched. Here the image is adjusted for various parameters such as image intensity levels, brightness and colour balance. These adjustments improve on the quality of the image which in turn yields better feature extraction. The enhanced image is then checked for intensity constraint in order to get the segmented area of vegetation and building. Considering the pixels $\mathrm{I_1, I_2, ..., I_N}$ in the image, whereeach of the pixels is defined by the intensity value and N is total number of pixels in the image. If the pixel value is above threshold set for building, then pixel is classified as building segment pixel and else, if the pixel value is belowthreshold set for vegetation, then the pixel is classified as vegetation segment pixels. Let the threshold for vegetation be set as $\mathrm{T_V}$ and threshold for building be set as $\mathrm{T_B}$, then

$$\begin{array}{l} \textit{if } I_j > T_B \textit{ where } 0 < j \le N, \textit{ then } I_j \textit{ is classified as Building area pixel} \\ \textit{else if } I_j < T_V \textit{ where } 0 < j \le N, \textit{ then } I_j \textit{ is classified as Vegetation area pixel} \end{array}$$

All the classified building area pixels combine to form building area segments and pixels classified as vegetation area pixels combine to form vegetation area segment.

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b) Segmentation of barren land

The segmentation of barren land from the satellite image is carried out by performing modified graph cut algorithm.Graph cut provides a clean, flexible formulation for image segmentation and provides a convenient language to encode simple local segmentation cues, and a set of powerful computational mechanisms to extract global segmentation from these simple localpixel similarities. Though these positives, graph cut algorithm still experiences lag due to certain disadvantages like metrication artefacts, shrinking bias and multiple labels. In order to remove these issues, we have used our modified graph cut algorithm. In the graph cut, the image pixels are interconnected to form the shape of a graph. In graph cut, theses interconnections are evaluated and a cut is made when two pixels differ by an amount. When a cut is made it forms to two segments and the process is continued to form segments. In our modified graph cut, apart from two pixels in consideration, all the neighbourhood pixels are also taken into consideration before the cut is made. Hence, it allows for having better segmentation results.

c) Road area segmentation

The road area is segmented from the satellite image by following the procedure as discussed below. The process is carried out in two phases and later the two phase results are combined to have the final road extraction.

In phase 1, the RGB image is converted to grey scale image and is then converted to black and white image with the aid of the threshold set. A grey-scale image is an image which is composed exclusively of shades of grey, varying from black at the weakest intensity to white at the strongest. The grey scale image is converted to the image to the binary format. Binary uses two states represented by the digits zero and one to encode information. A binary image is a digital image that has only two possible values for each pixel. Two colours used for a binary image are black and white. Binary encoding is carried out by converting the grey scale pixel to either black or white by fixing a threshold $\mathrm{T_{GI}}$. If the grey level intensity value $\mathrm{P_i}$ is less than the threshold set $\mathrm{T_{GI}}$, then its converted as black pixel that is having value 0, else converted as white pixel having value 1.

$$\text{if}\begin{cases}\mathrm{P_i} < T_{GI}\ \textit{then change}\ P_i\ \textit{to}\ 0\\ \mathrm{P_i} \geq T_{GI}\ \textit{then change}\ P_i\ \textit{to}\ 1\end{cases}$$

Hence the result from the phase 1 will either value 0 or 1 for each pixel.

In phase 2, the red and blue components of the RGB image are initially converted to zero and then greyscale converted. The grey scale image is then image adjusted where the image is enhanced through varying image intensity levels, brightness and colour balance. The adjusted image is then image rotated and done image convolution to yield a converted image. Each of pixels in the converted image is matched to intensity threshold value set and is converted to black and white image accordingly. If the grey level intensity value of the converted imagebe $\mathrm{G_i}$, then if the value less than the threshold set $\mathrm{T_C}$, then its converted as black pixel that is having value 0, else converted as white pixel having value 1.

$$\text{if}\begin{cases}\mathrm{G_i} < T_C\ \textit{then change}\ G_i\ \textit{to}\ 0\\ \mathrm{G_i} \geq T_C\ \textit{then change}\ G_i\ \textit{to}\ 1\end{cases}$$

As a result, from each of phase each pixel will be classified as either black or white where black is given a value 0 and white is given a value 1. Results from both phases are combined in an OR gate model to have the final pixel value. That is, when both the phases of the pixel have the value 0, then the output pixel value will be 0 and 1 in all other cases as shown in table 1. The final image based on the truth table will be truth table of which the roads part will be shown in black and hence, the road area can be segmented.

Table 1: Truth Table Model Form Two Phases

Output from phase 1	***Output form phase 2***	***Final output value***
0	0	0
0	1	1
1	0	1
1	1	1

3.3 Feature Extraction

After the segmentation by the modified graph cut theory, features are extracted from the segmented regions. Feature Extraction is of vital importance because on the basis of extracted features the fuzzy rule classifier will be trained and the final classification is carried out. The features extracted include standard deviation, entropy and variance.

Entropy of pixels in the segment (E) is computed by using the formula:

$$E = -\sum_j k_j \log_2 k_j$$

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Where, k_j is the probability that the difference between 2 adjacent pixels is equal to j, and Log $_2$ is the base 2 logarithm.

Mean of intensities of the corresponding segment is given by the formula:

$$M = \sum_{j=1}^{D} \frac{I_j}{D}$$

Where, I_j is intensity of the pixels of the image and D is the number of pixels in the segment.The variance of the intensity of the pixels of image can be calculated by formula given by:

$$M_{mn} = \sum_x \sum_y x^m y^n I(x, y)$$

In the training of the fuzzy rule classifier, the features are used. Features from different classes will be varying and classification is carried accordingly, where classes include barren land, building, road and vegetation.

3.4 Classification Using Fuzzy Rule Classifier

For the classification of the satellite image we make use of fuzzy rule classifier proper rules are incorporated to fuzzy classifier. The overall process of the rough-fuzzy classifier is divided into two steps, such as rule generation using rough set theory, and classification using fuzzy classifier.

In the first step, the training dataset which consists of features extracted from satellite images are given to the rough set theory, in whichinitially discretization is carried out where data processing to convert the data into specific interval is carried out. Then, relevant analysis is carried out using reduct and core process defined in rough set theory and computation of similarity is made. Then, the indiscernibility matrix of rough set theory is used to generate the fuzzy rules. In the second step, the fuzzy rules generated from the first step are given in the rule base of fuzzy classifier. Then, for the test dataset, the input is fuzzified and then, the fuzzified input is matched with the fuzzy rules defined in the rules base. Finally, the fuzzy score is generated after the defuzzification process to classify the satellite image into vegetation area, building area, barren and road area. The features given as input include area; perimeter, entropy, mean and information gain and the classified outputs include that of barren land, building area, vegetation area and road area.

The fuzzy membership function definition and fuzzy rule base are the two important steps in fuzzy rule classifier. Fuzzy Membership function is designed by choosing the proper membership function. In our case, triangular membership function is used to convert the input data into the fuzzified value. The Triangular membership function consists of three vertices a, b and c of $f(x)$ in a fuzzy set a where a is the lower boundary and c is the upper boundary where membership degree is zero and b is the centre where membership degree is 1. The membership function fully defines the fuzzy set and provides a measure of the degree of similarity of an element to a fuzzy set.Membership functions can take any form, but there are some common examples that appear in real applications.

The triangular membership values formula is given as below,

$$f(x) = \begin{cases} 0 & if \; x \le a \\ \dfrac{x-a}{b-a} & if \; a \le x \le b \\ \dfrac{c-x}{c-b} & if \; b \le x \le c \\ 0 & if \; x \ge c \end{cases}$$

Figure 2 shows a triangular membership function for a single fuzzy set. Here, we can see that at a and c the value is zero and it reaches steadily to a maximum of value one at the centre point b between the a and c. Figure 3 shows the plot considering all the four membership functions having overlapping values. Here, the curves for very low, low, medium and high are shown for a particular one attribute.

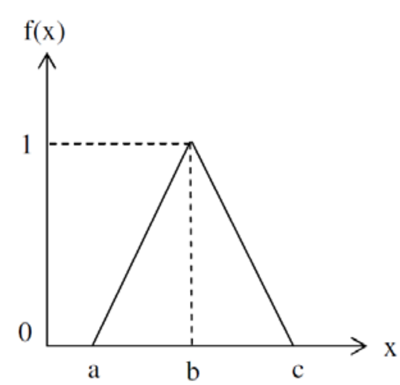

Figure 2: Triangular Membership Function

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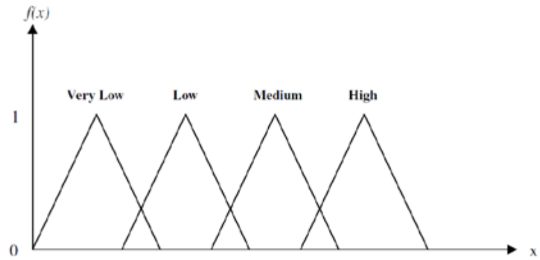

Figure 3: Triangular Membership Function With Defined Parameters And Their Values

Fuzzy rule base is generated by using rough set theory. The rule base contains a set of fuzzy rule in the form of, IF A2 is Low and A3 is HIGH, THEN decision is YES. Hence, the input satellite image is classified as barren area, road area, vegetation area and building area.

4. RESULTS AND DISCUSSIONS

The proposed technique for satellite classification evaluated and analyzed in this section. Section 4.1 gives the experimental set up and the evaluation metrics employed. The experimental results are discussed in section 4.2 and performance analysis is made in section 4.3.

4.1 Experimental Set Up and Evaluation Metrics

The proposed technique is implemented in MATLAB on a system having 6 GB RAM and 2.6 GHz Intel i-7 processor. The evaluation metrics used is the accuracy of the classification. The accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's actual true value.

4.2 Experimental Results

The experimental results obtained for the technique are given in this section. The original image is given in figure 4 and the greyscale converted image is given in figure 5. The contrast enhanced image is given in figure 6, building area in figure 7, empty area in figure 8, road area in figure 9 and vegetation area in figure 10.

Figure 4: Input Image

Figure 5: Greyscale Converted Image

Figure 6: Contrast Enhanced Image

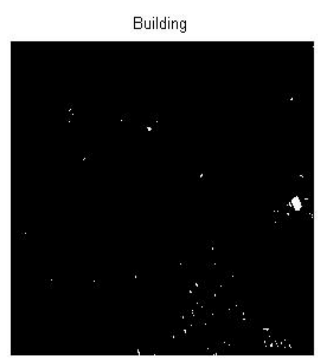

Figure 7: Building Image

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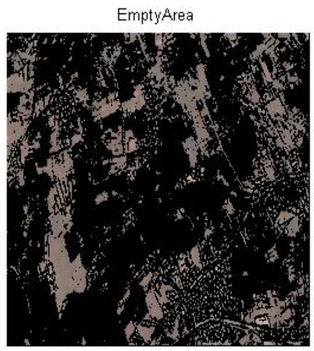

Figure 8: Empty Area Image

Figure 9: Road Area Image

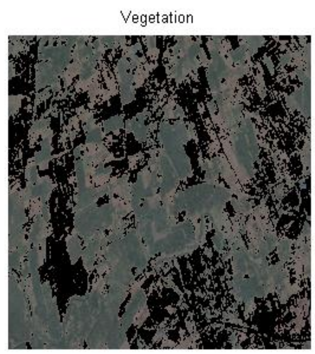

Figure 10: Vegetation Area Image

a) Perfomance Analysis

The performance is evaluated by the evaluation metric of accuracy. The accuracy obtained by the various classifications is given in the table 2 and figure 11. For calculating the accuracy, we have made use of many satellite images.

Table 2: Accuracy Values For Various Classifications

Classification Area	***Accuracy (%)***
Building Area	100
Empty Area	85.71
Road Area	89.71
Vegetation Area	94.83

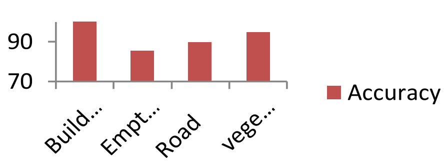

Figure 11: Accuracy Values For Various Classifications

We have also compared to the normal graph cut segmentation method which came about 79.77% accuracy and found that our modified graph cut bettered by an amount of 5.94%.

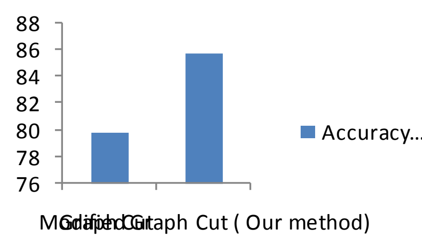

Figure 12: Plot Of Accuracy Values For Empty Land Classification

5. CONCLUSION

This paper presents a technique to classify the satellite images into barren land, vegetation area, building area and road area. At first, pre-processing is carried out and then it is segmented to have

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segments of barren land, vegetation area, building area and road area. The features of the segmented area are extracted and then final classification is carried out using fuzzy rule classifier. In the result section, classified output satellite images obtained are shown and proposed technique is evaluated by means of accuracy parameter. The accuracy obtained for building, barren land, road and vegetation are 100%, 85.71%, 89.71% and 94.83% so as to have an average of 92.56% accuracy. We also compare to normal graph cut segmentation method for barren land and from the results, it is proved that our proposed technique using modified graph cut have obtained better results of 85.71% in comparison to 79.77% .

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