Color Satellite Image Segmentation Using Markov Random Field and Multiresolutional Wavelet Transform

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***Abstract*—Image segmentation plays an important role in human vision, computer vision, and pattern recognition fields. Segmentation based on texture can improve the accuracy of interpretation. Satellite images are used in order to detect the distribution of classes such as soil, vegetation, built-up areas, roads, rivers, lakes etc. A problem that arises when segmenting an image is that the number of feature variables or dimensionality is often quite large. In this paper we used random field theory for identification of those classes and used multi resolution Haar wavelet transformation to put each pixel in desired class with great probability. Experiments are conducted on a set of 30 natural satellite texture images. A specific attention is paid to the use of Haar transform as a tool for image compression and image pixels feature extraction. Proposed algorithm is verified for simulated images and applied for a selected satellite image processing in the MATLAB environment.**

***Keywords*- random field theory, multi resolution analysis, texture, wavelet transformation**

I. Introduction

Image segmentation is an essential early vision task where similar featured pixel are grouped together to create homogeneous regions. A broadly used class of models is called cartoon model which often has simplified regions with specific colors, and often has obvious edges to convey semantic regions. Texture analysis occupies an important place in many tasks such as scene classification, shape determination or image processing. Although formal definitions of texture vary in the literature, it is commonly accepted that textures are naturally extracted and recognized as such by the human visual system, and that this analysis is performed in the frequency domain. The vast majority of the methods proposed in the literature provide good characterization of texture in controlled environments. In order to better describe textures, features must capture the nature of the texture, invariant to rotational, shift, and scale transformations. This paper describes the technique of wavelet transform use for multi resolution analysis associated with individual image pixels. Considering that the Haar functions are the simplest wavelets, these forms are used in many methods of discrete image transforms and processing. The method described is used for description of the whole system enabling perfect image reconstruction. The proposed algorithm of the Haar wavelet image decomposition includes image feature based segmentation. Recent work includes a variety of techniques: for example, stochastic model based approaches [1], [2], [3], [4], [5], morphological watershed based region growing [9], energy diffusion [6], and graph partitioning [7]. Quantitative evaluation methods have also been suggested [8]. However, due to the difficult nature of the problem, there are few automatic algorithms that can work well on a large variety of data.

In this paper satellite data are processed through the activity of a human operator for carefully selection of training pattern, which using RGB or HSV filters tries to identify several classes of elements appearing on them. These classes are therefore a way to group homogeneous land features, such as vegetation area, urban area and water area. A fully functional system is created for segmentation purpose.

II. Feature Extraction

First, we describe the texture and color features extracted from the input image $\mathcal{I}$. An image is defined over a finite three dimensional matrix $\mathcal{I}(x, y, z)$ where x and y denoted the height and width of the image and z will store the color information. At each pixel of training samples various observations $\mathcal{F}$are calculated which is the input of our algorithm.

A. Color Features

The most important problem for color image is to measure calculable color difference between any two random colors. Various experimental evidences suggest that the RGB color space may be considered as a Riemannian space [13]. Due to the complexity of determining color distance in such spaces, various formulas are proposed by various organizations. These formulas approximate the Riemannian space by a Euclidean color space yielding a perceptually uniform spacing of colors. We use CIE-L*u*v [13] formulas to create our color space. Fig1 shows the difference between RGB CIE-L*u*v* color metrics.

B. Texture Features

Texture means patterns with properties of homogeneity that do not result from the presence of colors [14]. Contrast, uniformity, coarseness, and density are typical texture features, statistical based and transform based are two basic class of texture descriptor. We only used statistical based for texture which explore grey level spatial dependence of textures to extract some statistical features which is used as texture representation. One of the techniques is Gray-Level Co-occurrence approach (GLCM) which we used here. GLCM uses grey level co-occurrence matrices whose elements are the

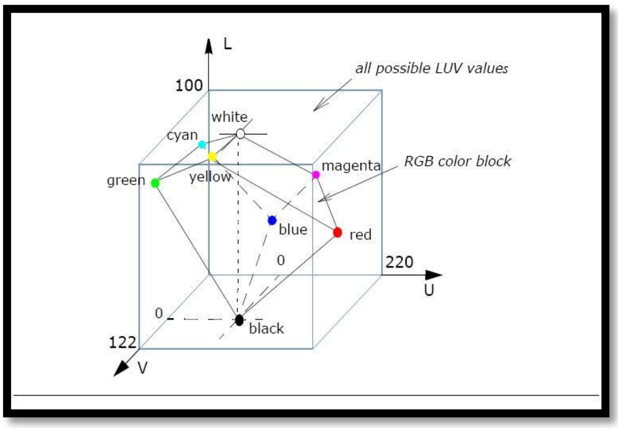


*Fig. 1: difference between RGB and CIE L*u*v color space*

relative frequencies of occurrence of grey level combinations among pair of image pixels. GLCM considered the relationship of image pixel in different direction such as vertical, horizontal, diagonal and anti-diagonal. GLCM include second order grey level information, which is mostly related to human perception and the discrimination of texture [15]. Three statistical features of GLCM are computed. The features are energy, entropy and contrast. $G \times G$ GLCM for a displacement vector $d = (dx, dy)$ is defined as follows. The (i, j)in R_d is the number of occurrence of the pair of gray-level $i$and j which are a distance d apart. The texture features used here are listed as follows:

$$Energy = \sum_{i=1}^{N} \sum_{j=1}^{N} R_d^2\,(i, j). \quad (1)$$

$$Entropy = -\sum_{i=1}^{N} \sum_{j=1}^{N} R_d(i, j) log R_d(i, j). \quad (2)$$

$$Contrast = \sum_{i=1}^{N} \sum_{j=1}^{N} (i-j)^2 R_d(i, j). \quad (3)$$

III. MRF SEGMENTATION MODEL

Markov random field theory is a branch of probability theory for analyzing the spatial or contextual dependencies of physical phenomena. It is used in visual labeling to establish probabilistic distributions of interacting labels. As discussed in section I, the segmentation is obtained as cartoon image, which is basically a labeled image of input image $\mathcal{I}$. Hence for each pixel i.e. $\mathcal{I}(x, y)$ the class type that the pixel belongs to is specified by a class label which is a discrete random variable of predefined class labels £=(1,2, … L) and derived from the training image. The set of these labels is denoted by s .Moreover the observed image feature (color and texture) are supposed to be a realization from another random field which is a function of label set s. basically the image process represents the apparent behavior of underlying label process. Our goal is to find the optimal labeling which maximizes the posterior probability $P(s|f)$ that is the *maximum a posteriori (*MAP) estimate [2] where f is the set difference of unused site.

A. Labelling process

The labeling process s is modeled as a Markov Random Field with respect to a second order neighborhood system shown in fig.2. According to the *Hammersely – Clifford theorem* [3], $P(s)$follow a Gibbs random field on site S

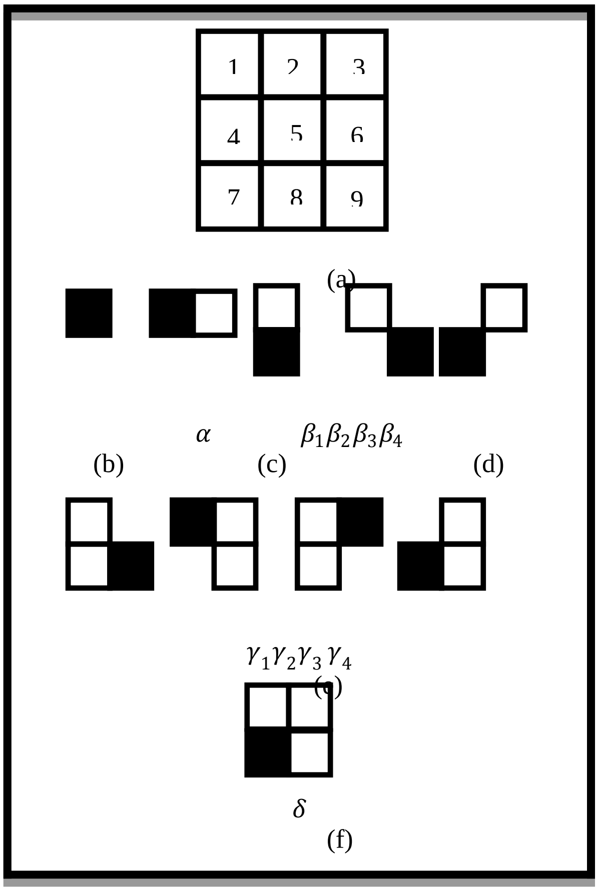


Fig. 2 second order neighborhood system in (a) and (b: single site), (c and d: double site), (e: triple site) and (f: Quadruple site) showing the possible cases of sites

$$P(s) = Z^{-1} \times e^{-\frac{1}{T}U(f)} \quad (4)$$

Where

$$Z = \sum_{f \in £} e^{-\frac{1}{T}U(f)} \quad (5)$$

is a normalizing constant called the partition function, T is a constant called the temperature, which shall be assumed 1in our case and $U(f)$ is the energy function. The energy

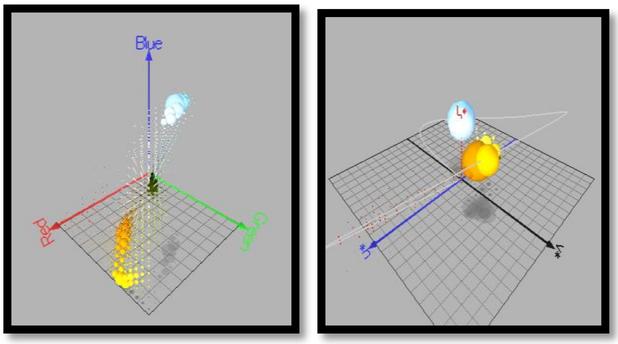
$$U(f) = \sum_{c \in C} V_c(f) \quad (6)$$

is a sum of clique potentials $V_c(f)$ over all the possible cliques C. The value of $V_c(f)$ depends on the local configuration on the clique c. here we use -1 is the all the pixel of neighborhood are matched with the desired pixel else the value of c is +1.

Note that this energy is proportional to the length of region boundaries. Thus, homogeneous segmentations will get a higher probability.

B. Image processing and posterior energy calculation

Multivariate normal density model is appropriate for most of the classification problem. Samples of this type of distribution clustered around the mean of the sample class in which variance show the spread out area of that class. Texture feature image are created such that similar intensities map to similar intensities. Hence the pixels of same textures are assigned a predefined value with some variance from CIE-L*u*v* colors in Euclidean space [1]: pixels with similar color map to CIE-L*u*v* values that are close to their average shown in fig.3.



(a) (b)

*Fig.3: Color histogram of RGB image in (a) and CIE-L*u*v* image in (b)*

We can clearly see the color histogram of RGB distributed all over the axis with different colors while in CIE-L*u*v* a cluster is formed for every color. Hence, region is formed where there is any discontinuity either in the colors or in texture. The whole posterior can be expressed as a second order MRF by calculating the contributions of likelihood terms of various sites. After this the segmentation problem is reduced to maximizing posterior probability and reducing the Gibbs sampler function.

IV. WAVELET TRANSFORMATION

Signal wavelet decomposition using Discrete Wavelet Transform (DWT) provides an alternative to the Discrete Fourier Transform (DFT) for signal analysis resulting in signal decomposition into two-dimensional functions of time and scale[9][10][11]. The main benefit of DWT over DFT is in its multi-resolution time-scale analysis ability. In our paper we use Haar wavelet transform for multi-resolution analysis. The reason for choosing Haar is its simplicity. In multi-resolution analysis the mother image is reduced into sub images by dropping done the resolution by a factor of 2. We are only used the LL that is low pass filter image to both row and column. These multi-resolution wavelet transformations create the tiles of image at various resolutions which is used in deciding the values of pixel [12].Multi-resolution image structure is shown in fig 4.

V. METHODOLOGY

We are using blue marble satellite high resolution image generated by NASA and would be free to download up to the level of 1pixel/km. Before done the actual segmentation we have to prepare the training text file which contains the description of all the classes defined in training and also all the texture and color features. The training file we created will remain same for the images of same type i.e. contains same type of classes. The algorithm for segmentation of image is shown below.

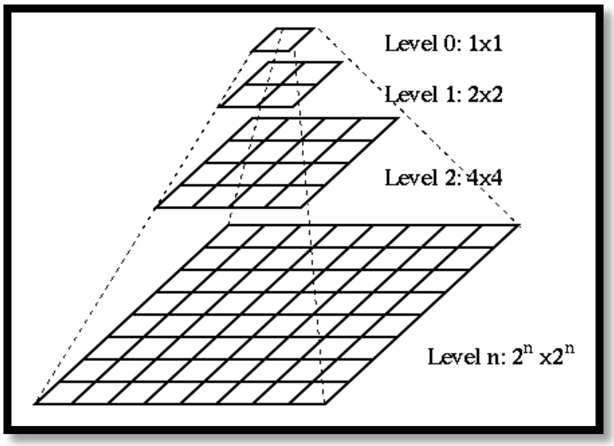


Fig.4: multi-resolution image shows at various levels

- *Preprocessing*

  Target image is taken as an input from the user then the whole image is converted from RGB to CIE-L*u*v* format for comparing the color feature. The target image is also converted into the grey scale for comparing the texture feature. Also an additional pixels rows and column is added depends on the neighborhood system for calculating the feature of the boundary variables.

- *Prior probability calculation*

  On the basis of 3×3 neighborhood system each pixel color and texture feature is computed and compare it with the training file for initial label of classes in which the pixel lies. Assign the class label to the pixel with a fixed prior probability i.e. 0.001 in our case.

- *Posterior probability calculation*

  On the basis of second order neighborhood system of *Markov Random Field* calculate the posterior probability of image from the prior probability and clique potential of the neighborhood and maximize the joint probability. This step is repeated till there is not more than predefined threshold value change in the pixel label or its posterior probability.

- *Preprocessing before multi-resolution tranformation*

  Wavelet transform takes the image into the power of 2^n we have to take care of it also the resolution of satellite image is very high so for using the maximum allowable size of image will also take a lot of time. So we cut the image into the predefined maximum size i.e. 512×512 pixel with some overlapping region for saving any loss in mosaic.

- *Multi-resolution wavelet transformation*

  The various overlapped image of target image would undergo *Haar Wavelet Transform* from level n to level3 i.e. 2^n *to* 2^4 and each level is constructed again back to level n. This will give us a maximum of six image of each single image of targeted image with each image at different resolution will be used as input for next step.

- *Muti-resolutional markov random field*

  These images are again used for maximizing posterior probability but in pyramid neighborhood system with a different clique potential at each level and then maximizing the posterior probability and create the image of n level. Then regroup those entire $n^{th\ level}$ images into a single image of our initial size and save them on disk.

This whole procedure is automated after agreed upon on some initial parameters. A brief representation of this methodology is defined in flow chart shown in fig.5.

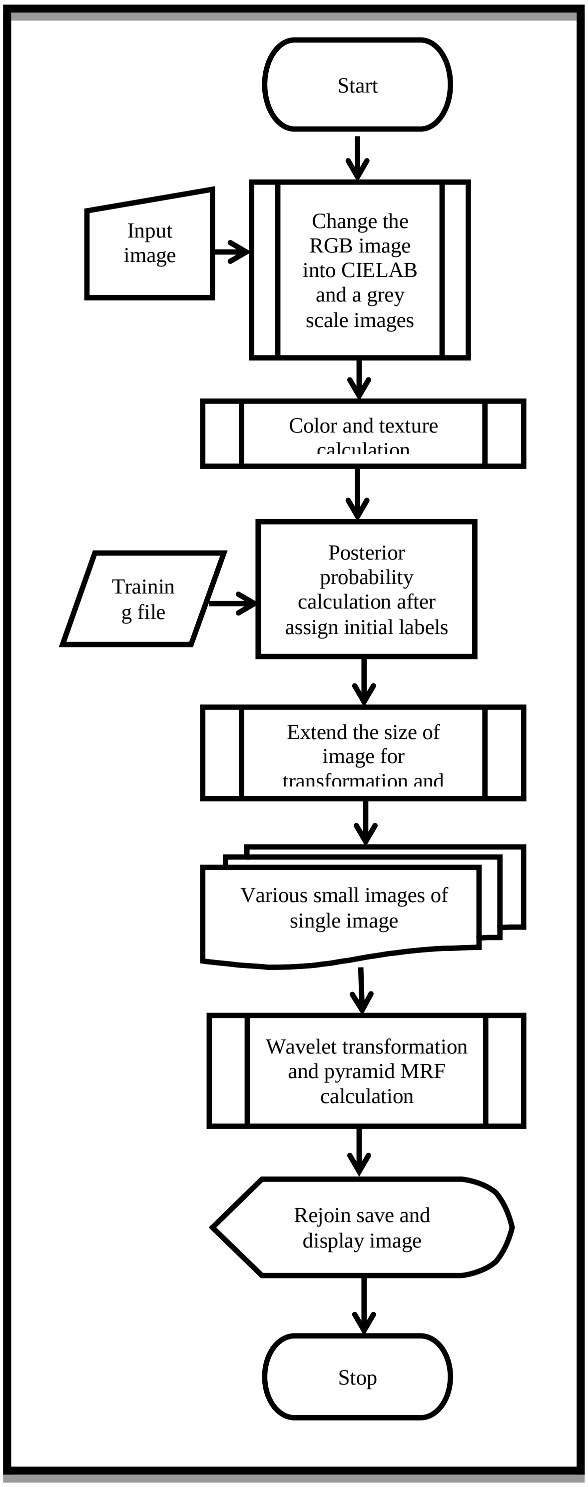


Fig.5: Flowchart shows methodology of segmentation

VI. RESULT

This approach shows good results in satellite image segmentation given a very clear cartoon model like clear sharp region where we easily discriminate various classes of our images. This approach is also removing those areas that are not necessary when representing a whole region for ex. a island in sea which is small with respect to the image. We have done our comparison on about 200 satellite images of various level of resolution and used same training file for all images having same set of classes. Here we present a satellite before and after segmentation of images these images are shown in fig. 6 and 7. Here we use only four classes to segment the targeted image.

Fig 6: Input image for segmentation

Fig. 7: Segmented image after segmentation

VII. Conclusion and Future Work

Although we can see that it give us very good result when segmenting the image but still we found that there is a scope of improvement in it. We are not still able to segment those places properly whose colors are nearly same and also the texture property on grey scale is same. So we are trying to extend our approach of GLCM on color images to segment images more precisely and also try to use various other transformations and try to compare the results to get the best from it.

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