Retrieval of Remote Sensing Images using Fused Color and Texture Features with K-means Clustering

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Abstract **In the advancement of remote sensing satellite sensors, a large number of high-resolution satellite images are captured every day. To retrieve the required images from a large database has become a challenge. Here, we have used fused color and texture feature for retrieving remote sensing image. Here, we used HSV Histogram, Color moment and color autocorrelogram for color feature extraction. A wavelet transform is used for texture feature extraction. These combined color and texture are used for indexing using k-means clustering. Manhattan distance is also used for similarity matching. UC Merced Land use Land Cover Dataset has been used for the experiment. The k-means clustering with combined color and texture features has shown better retrieval performance than only color features. Indexing has been done using Manhattan distance and k-means clustering. K-means clustering gives better retrieval performance than Manhattan Distance.**

Keywords ***color moment, color autocorrelogram, wavelet transform, K-means clustering.***

I. INTRODUCTION

Many Images are obtained from the satellites. These images cover the large amount of geographical area such as forest, urban areas, water bodies etc. The information in remote sensing images used in many application like in agriculture, land cover mapping, urban monitoring and planning, defense and many more. The database of remote sensing images is increasing every day. Hence there is difficulty to extract important information from large database. Hence to retrieve required images from large database is a challenge. Traditional image retrieval methods use keywords matching [1], like time of acquisition of image, type of sensor and location. But traditional methods have many disadvantages. To avoid the disadvantages of traditional methods of image retrieval, content based image retrieval methods are evolved. The low level features color, texture, shape, spatial and spectral has been used for retrieving the image from database [2, 3]. Feature extraction is an important method for content based image retrieval system. Features extraction means extracting key features of image. Color, texture, shape and spatial features have been used for retrieval of images. These extracted features are used for indexing. Now this indexing can be used for retrieving image from the database. In this paper, color and texture features have been used for retrieval of image from database. Color Moments, Color Histogram, and color AutoCorrelogram are used for extraction of color feature and wavelet transform is used for texture feature extraction. K-mean clustering is used for indexing. Experiments are carried on separate and combined features.

II. RELATED WORK

In the literature, different methods are found for retrieving content based remote sensing images. In [4] three methods are used for content-based image retrieval. First method is attribute method. Here images are stored in the database with their metadata which describes their information like date and subject. The second method is a textual feature in which images are retrieved using textual description. This feature is more flexible but it has the drawback that it gives fuzziness in textual and natural language when describing images. Last method author has used contents of images as a feature. Luis M. Del at.al[4] has been used color and texture feature as a pattern of an image as a feature for image retrieval.

A most important feature of an image is color which is extensively used for retrieving the image. Color is invariable to complexity. Color images are more sensitive to human eyes than the grayscale images. The color moment, color histogram, and color coherence vector etc. are widely used techniques for color feature extraction. A color histogram has generally used for distributions of a color of an image. The histogram feature of the query image and data image has extracted and compared using a similarity metric for image retrieval. This method is not useful when the color distribution of two different images is the same. The color moments extracts the pixels with color distribution and spatial information from the images. Hence color moment gives refinement in image retrieval than a color histogram. Color moments [9] have used as a data object for clustering similar image. An only color moment cannot give the best retrieval result. To get the best retrieval result color moments and color histogram has used as a combined feature.

Spectral unmixing has been used in [5] for retrieving hyperspectral images effectively. In the Prototype system [6] color and texture combined features are used for retrieving the image. In [7] color, texture, spectral feature and spatial features are used for remote sensing image retrieval. Local invariant features [8] are used for land-use/land-cover image retrieval. In [8] bag-of-visual-words (BOVW) have created using grid-based local feature extraction. Here codebook has created using a clustering algorithm. This codebook has been used for retrieving the image. In [9] histogram of gradients and 3-dimensional

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local binary pattern has used for remote sensing image retrieval. Here an image features have extracted using 3D-LBP then wavelet transform has applied after that HOG is used to find feature vector of the image. Steerable Pyramids with CIElab color systems and RGB [10] has used for retrieval of remote sensing images. In this paper, the image has decomposed into sub-bands and then statistical measures have calculated for generating texture features [10]. In [11] attribute profiles has used for indexing remote sensing images and retrieval of images.

III. Methodology

The proposed method consist of multi-feature extraction technique in which color moment, color histogram and texture features are used to generate feature vector. The overview of system is in figure 1.

A. Feature Extraction Techniques

Any CBRIR uses the image contents color and texture features for indexing the image and to access the image. The CBRIR system architecture is shown in fig. 1. Generally, any CBIR systems extract color, texture, and shape features from database images. This feature of an image is also called as the signature of an image. There are generally two features 1) Global 2) Local. The global features are color and texture histograms of the whole image, whereas local features are color, texture feature of sub-image or region of interest. In the literature, different methods are available for extraction of low-level features of images. In this CBRSIR color and texture features of images has been used for retrieval of an image from the large database.

1) Color Features: Most frequently used a visual feature for image retrieval is Color [13, 14, 15]. Color consist of three-dimensional values, hence it makes classification of a image better than single dimension gray level value.

a) Color Histogram: This is an extensively used technique for color feature extraction. A Color histogram shows frequency of pixel of each color within the image. Commonly used color histogram methods are i) Global Color Histogram (GCH) ii) Local Color histogram (LCH). The global color histogram represents the statistical color frequency in the whole image. The distance between color histograms has been calculated to find the similarity between the two images using GCH.

Local color histograms (LCH) divide the image into blocks and determine the color histogram of each block. To find the similarity between two image color histogram of one block of one image will be compared with a color histogram of a block of the second image at same location.

Color consists of three chromatic attributes of an image. Color based images have three color spaces RGB, CMY and HSV. Among these three color spaces, appropriate color space is used to identify the image. RGB color space does not give the result as per the visual requirement of human, so RGB color model is converted into another color model. HSV color model has been used in this paper. HSV histogram uses three steps for feature extraction: (1) conversion of color space (2) Quantization of color and (3) computation of histogram. In color space conversion RGB input image is translated into HSV color model. Colors in HSV are differentiating by hue, saturation and value.

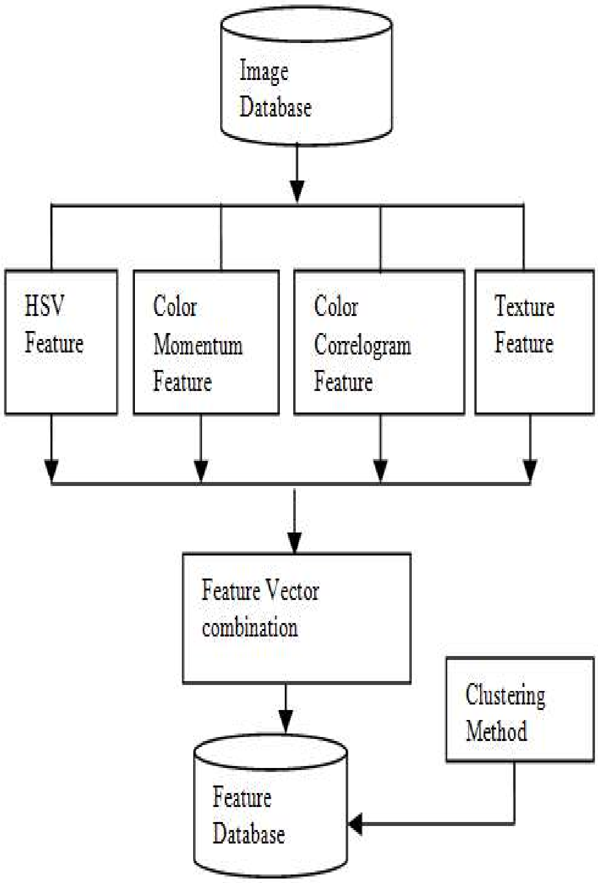

Fig.1 System Overview

In HSV color model hue decides color, Saturation decides intensity of color and value decides brightness of color. Color space conversion of RGB to HSV is as follows:

$$H = \cos^{-1} \frac{{}^{1}\!/_{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \tag{1}$$

$$S = \frac{3[\min(R;G;B)]}{R+G+B} \tag{2}$$

$$V = \left[\frac{R+G+B}{3}\right] \tag{3}$$

The HSV plane is as shown in fig.2.

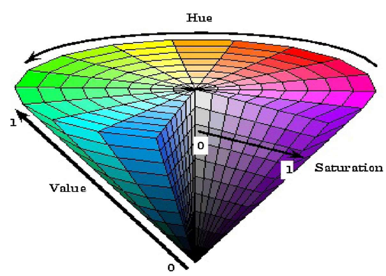

Fig.2. HSV Plane

b) Color Moments: Color moments are describes the probability distributions of colors in animate. Here Color moments are used for indexing images. In [13] author has used three moments to find the color features. Mean, Variance and Skewness are the important parameters of color moments[13]. The following color moments are used to find color feature.

Moment 1: Mean[13]

$$E_i = \sum_{N}^{j=1} \frac{1}{N} p_{ij} \tag{4}$$

Where $p_{i,j}$ determines j^{th} the pixel value at i^{th} color channel and the total number pixels in the image are N[13].

Moment 2: Standard Deviation [13]

$$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{N}^{j=1}(p_{ij} - E_i)^2\right)} \tag{5}$$

Moment 3: Skewness [13]

$$s_i = \sqrt[3]{\left(\frac{1}{N}\sum_{N}^{j=1}(p_{ij} - E_i)^3\right)} \tag{6}$$

c) Color Correlogram: Color Correlogram is used for finding the spatial correlation between pair of colors which changes with distance[12]. As complexity of color correlogram is more, so auto correlogram can be used image indexing [12]. To find color correlogram consider an image I of size $m \times n$. Consider two pixels P1 and P2 with its color C_1, C_2 respectively. The distance between C_1, C_2 is d. Probability of pixel C_i at a distance d from pixel C_j can be calculated by following equation.

$$\gamma_{C_i}^{(d)}(I) \equiv \Pr[|\, p_1 - p_2 \,| = d, p_2 \in I_{C_i} \mid p_1 \in I_{C_i}] \tag{7}$$

Consider P1=(x1, y1) and P2=(x2, y2) are two pixels. The Distance between two pixels has been calculated by (8).

$$|P1 - P2| = \max\{|x1 - x2|, |y1 - y2|\} \tag{8}$$

An auto correlogram of image I is finding probability of identical colors (c_i, c_j) in Eq.(7) at distance d. [12].

2) Texture Feature: This is is one of the feature for image retrieval for large scale high resolution images. Color feature always occurs over a pixel where as texture occurs over a region. Sometimes spectral information is insufficient remote sensing data. Then texture features of such types of images are important to classify the images or data. There are four types of texture analysis techniques viz. structural, statistical, filter based and Transform. Mathematical morphology is an example of structural technique. Gray level co- occurrence matrix belongs to statistical technique. Gabor filters is an example of filter based technique.

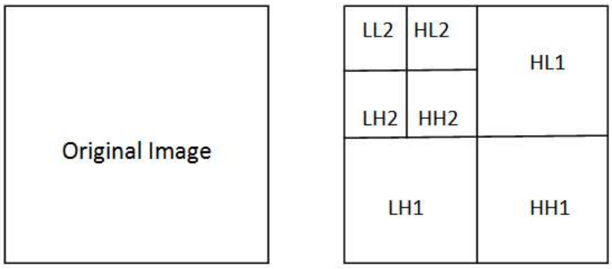

Fig 3: Wavelet Decomposition

Wavelet is a transform based methods. Here wavelet method is used for texture feature extraction.

a) Wavelet Transform: The DWT is an efficient method in high resolution images to extract features. The discrete wavelet transform (DWT) is implemented by Mallat s tree algorithm [16] by applying linear filtering iteratively. The wavelet transform is very robust and effective method for texture feature analysis. In wavelet transform series of functions are obtained by decomposing input signal [16]. These functions are called as wavelets and scaling. Base function of wavelet is called as mother wavelet shown in (9). Scaling and translation is applied on this base function.

$$s \in R^+ \quad u \in R \qquad \psi_{s,u}(x) = \frac{1}{\sqrt{s}}\psi\left(\frac{x-u}{s}\right) \tag{9}$$

where s indicates the scaling and u indicates the translation. The wavelet is decomposed by applying each of the elemental functions or wavelets to the original function[16]:

$$Wf(s,u) = \int_R f(x)\frac{1}{\sqrt{s}}\psi^*\left(\frac{x-u}{s}\right)dx$$

Generally, wavelets are used as high-pass filters, while scaling is used as low-pass filters. The original image has been divided into sequence of images by applying wavelet transform. Theses sequence of images has different scales, called as trends and fluctuations [16]. The trends are used as average of actual image. Hence trends are used as low pass filter where as fluctuations are used as high pass filter. The required information lost in low pass filter. Therefore fluctuations are used to find texture features [22]. To get reconstructed images inverse transform function is applied to the fluctuations. Then horizontal, vertical, and diagonal three reconstructed images are obtained [22]. In the wavelet transform original image is decomposed into four sub images. In the first level of transformation the original image is decomposed into LL1, HL1, HH1, and LH1 as shown in fig 3. LL1 is called as low pass sub image and HL1, HH1, and LH1 are called as high pass sub image. In the second level transformation the low pass sub image (LL1) is again decomposed into four sub images [22].

B. K-means Clustering

Clustering is grouping the similar objects into one cluster and dissimilar objects into the other clusters [20]. In 1967, MacQueen firstly proposed the k-means algorithm [20]. The basic k-means algorithm working is as follows in[20].

1. Select the k clusters randomly.

2. Select the centre points for each cluster.
3. Calculate the data object distance from centers of cluster using Euclidean distance function.
4. Assign the data object to the closest cluster according to step 3.
5. Mean of data object is recalculated in each cluster.
6. Repeat steps from 2 to 5 until mean of data object is not changed.

IV. Results and Discussion

For experiment we used land use image dataset [18], with 21 classes and each class consist of 100 images. Each image in data set is of size 256 × 256 pixels with 30 cm pixel resolution [18]. The images from the dataset belongs to one of the following classes: agricultural, baseball, airplane, diamond, building, beach, chaparral, forest, dense residential, golf course, intersection, harbor, mobile home park ,medium density residential, parking lot, overpass, river, sparse residential runway, sparse residential, tennis courts and storage tanks. The examples of Land use Land cover dataset is shown in Fig. 4.

In query by example technique we need to retrieve similar images. Similarity between two images is calculated by comparing feature vector of query image and database images. Here Manhattan Distance is used to calculate similarity measure [19]. The results are compared with K-mean clustering. The Manhattan distance D(x,y) is obtained by following mathematical equation[19].

$$D(X_i, Y_i) = \sum_{i=1}^{n} \left(X_i - Y_i \right). \qquad (9)$$

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TABLE I PRECISION AND RECALL FOR COMBINED COLOR TEXTURE FEATURE

Class	Color Feature(HSV+CM+ACO) +Texture Feature(Wavelet)				Color Feature(HSV+CM+ACO)			
	Precision		Recall		Precision		Recall	
	L1	K-Mean	L1	K-Mean	L1	K-Mean	L1	K-Mean
Beach	0.2	0.5	0.33	0.83	0.2	0.33	0.3	0.5
Tennis court	0.2	0.4	0.4	0.8	0.2	0.3	0.4	0.6
Agriculture	0.2	0.5	0.3	0.7	0.1	0.4	0.14	0.57
harbor	0.3	0.4	0.6	0.8	0.2	0.3	0.4	0.6
freeway	0.3	0.4	0.6	0.8	0.1	0.3	0.3	0.6
mobile home park	0.3	0.5	0.42	0.7	0.2	0.3	0.29	0.43
River	0.2	0.4	0.4	0.8	0.1	0.3	0.2	0.6
Medium Residential	0.3	0.5	0.6	0.8	0.2	0.3	0.33	0.66
Forest	0.4	0.5	0.6	0.83	0.3	0.4	0.5	0.6
Dense Residential	0.2	0.3	0.5	0.75	0.1	0.2	0.25	0.5

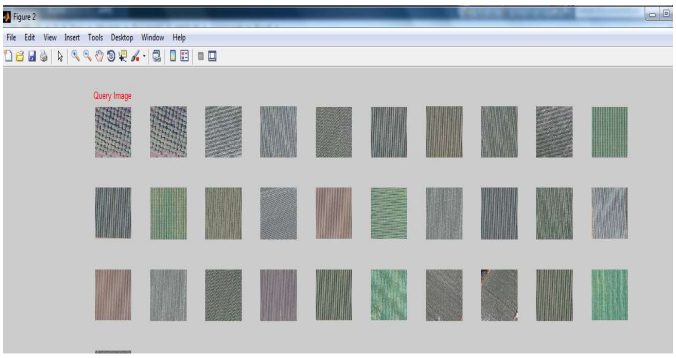
Fig 4. UC Merced LULC data set Examples

Precision and recall are two metric to measure the performance of retrieval system [21]. Precision P and Recall R are as follows:

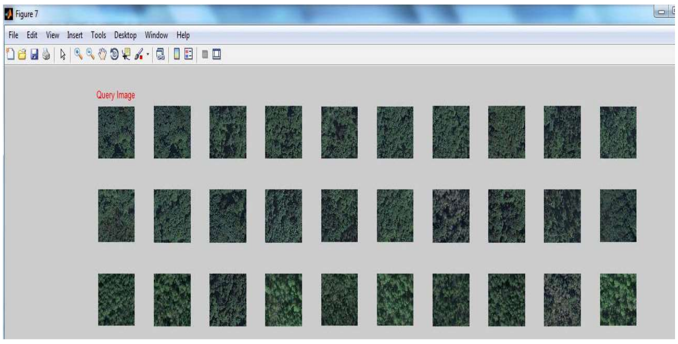
$$P = \frac{\text{Number of relevant images retrieved}}{\text{Total Number of images retrieved}} \qquad (10)$$

$$R = \frac{\text{Number of relevant images retrieved}}{\text{Number of relevant images in database}} \qquad (11)$$

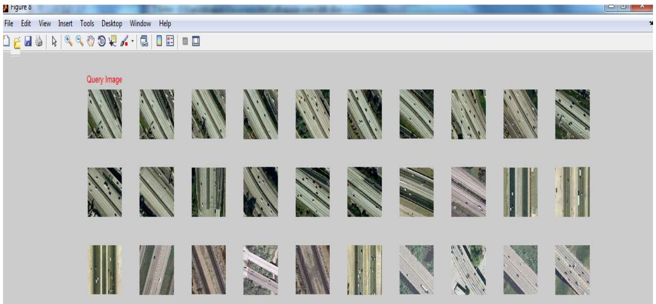
Here indexing also done by K-means clustering. So retrieval performance is measured for Manhattan distance and K-means Clustering also. Table I. shows that precision and recall for three color feature and texture feature using DWT. Results show that K-mean clustering gives better performance than Manhattan distance metric. Here performance is also measured by using only color features like color moments, HSV Features. Also performance is measured by combining color features which is calculated by three methods viz. color moments, HSV feature and color AutoCorrelogram. Result shows that combined color features give the better result than single features. Again performance is measured by combining color as well as texture feature. Results show that combined color and texture feature gives better performance than combined color features. Fig 5.shows retrieved images using combined color and texture feature. Comparison results of these methods are shown in fig. 6. and fig.7.



a)Agriculture



b) Forest



c) Freeway

Fig. 5 Examples Of images Retrieved Using HSV, Color Moment, Color Correlogram and DWT Feature a) Agriculture b) Forest c) Freeway

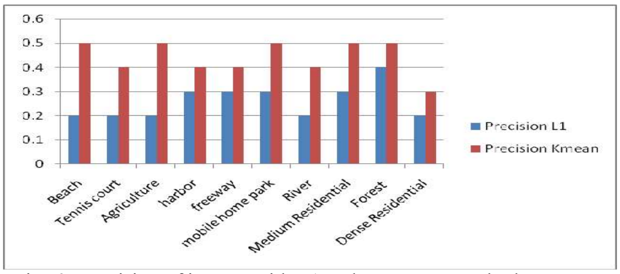


Fig. 6. Precision of images with L1 and K-means method.

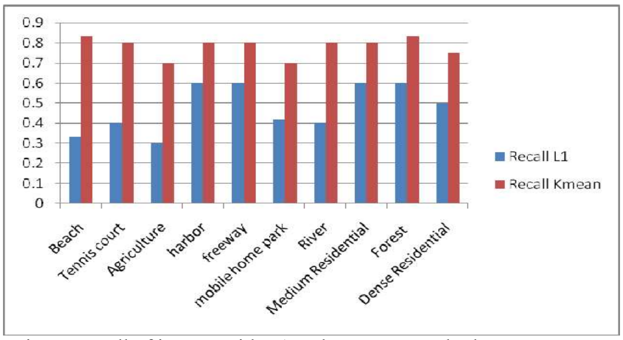


Fig. 7. Recall of images with L1 and K-means method

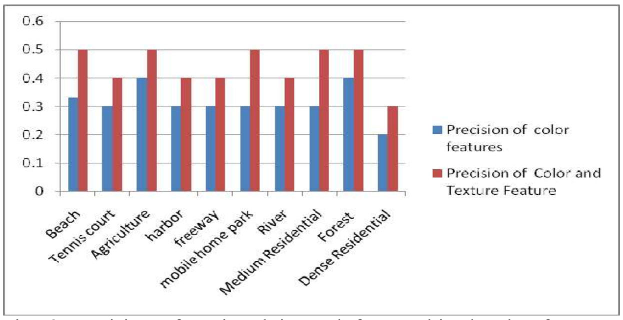


Fig. 8 Precision of retrieved imaged for combined color features and combined color and Texture Feature

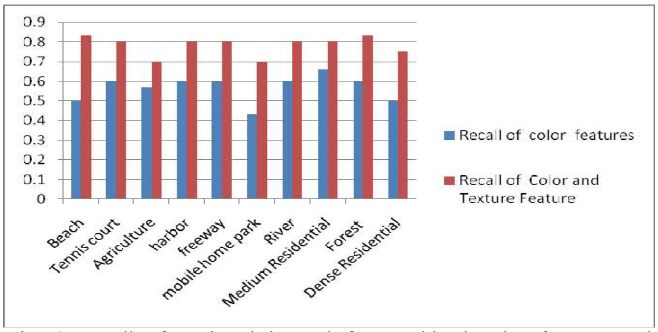


Fig. 9 Recall of retrieved imaged for combined color features and combined color and Texture Feature.

V. Conclusion

We have proposed content-based remote sensing image retrieval using the color feature and combined color and texture features. Combined color and texture feature gives better results than combined color features. K-means clustering is used for indexing which gives better results than Manhattans distance. Here for texture feature, we have used wavelet transform. In future, we extend our work by considering all wavelet types for texture feature extraction. We will add one more feature like shape with color and texture feature to improve the retrieval performance.

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