

# Geographical Image Retrieval

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**Abstract:** *The project design is a user-friendly and effective system for the task of land-use/land-cover (LULC) recommendation where the goal is to automatically provide the user with information about the object or event depicted in an image and the surrounding where the image was taken. The system improves the image viewing experience by presenting supplementary information such as location images and geographically nearby images. The information is automatically collected from the databases various sources on the Internet based on the SIFT and GLCM methods.*

**Keywords:** *Image retrieval, Land use Land Cover, Scale invariant feature transform(SIFT), Gray Level Concurrence Matrix GLCM.*

## 1. Introduction

Geographic image retrieval (GIR) or geographical image retrieval is the augmentation of information retrieval with geographic metadata. Information retrieval generally views documents as a collection or 'bag' of words. In contrast, geographic information retrieval requires a small amount of semantic data to be present (namely a location or geographic feature associated with a document). Because of this it is common in GIR to separate the text indexing and analysis from the geographic indexing. GIR systems can commonly be broken down into the following stages: GeoTagging, text and Geographic indexing, data storage, geographic relevance ranking (wrt a geographic query) and browsing results.

Geographic image retrieval lead to increasing availability of geographic context for the picture, videos and audio users share on the web. Such data has allowed systems to search through, browse and analyze media according to location without being wholly dependent on expensive manual annotation. However, the current extent of much geographic metadata consists of describing a single pair of coordinates per item. Here it investigates local invariant features for geographic (overhead) image retrieval. Local features are particularly well suited for the newer generations of aerial and satellite imagery whose increased spatial resolution, often just tens of centimetres per pixel, allows a greater range of objects and spatial patterns to be recognized than ever before. Local invariant features have been successfully applied to a broad range of computer vision problems and, as such, are receiving

increased attention from the remote sensing community particularly for challenging tasks such as detection and classification. So an extensive evaluation of local invariant features for image retrieval of land-use/land-cover (LULC) classes in high-resolution aerial imagery. Therefore, the raise of real-time building recognition or retrieval system becomes a challenging problem. The most recent approaches are to

recognize buildings by the street-view images; however, the query photos from mobile devices usually contain different lighting conditions. In order to provide a more robust city-view image retrieval system, we propose different systems for retrieving query images. There are two methods for capturing information on land cover

- (i) field survey
- (ii) analysis of remotely sensed imagery.

In field survey one has manually analyze the field and after that can give suggestions . But later one is better as is more fast for huge acres of land .Here aerial images plays a vital role here in the land use and land cover as it provides a complete picture for forest , agriculture land, buildings.

Application areas includes-

- Surveying: geographic location and data analysis including high-resolution asset location mapping.
- GIS: geographic location, data analysis and presentation for asset management.
- Extensive evaluation of local invariant features for image retrieval of land-use/land-cover (LULC) classes in high-resolution aerial imagery.
- Vehicle navigation: installed in anything from commercial passenger cars to tanks.

## 2. Proposed Work

The system will take any query image as a query and will search in its database about that place with that additionally the system is showing the similar images to the user. The database consists of geographic images. The images will be selected from the dataset and comparison takes place by calculating Euclidean distance between the query image and dataset images.

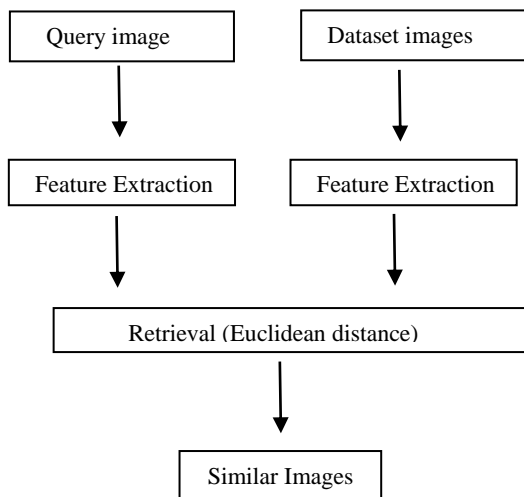


Figure 1. Block diagram of detailed geographical image retrieval system

The system is using GLCM (Gray Level Concurrence Matrix) and SIFT (Scale Invariant Feature Transform) for extracting features of the query image.

### 3. Dataset

The data set consists of images of 23 LULC classes selected from aerial orthoimagery with a pixel resolution of 30 cm. 1000 images measuring 256 by 256 pixels were manually selected for each of the following 23 classes: agricultural, airplane, baseball diamond, beach, buildings, chaparral, dense residential, forest, freeway, golf course, intersection, medium density residential, mobile home park, overpass, parking lot, river, runway, sparse residential, storage tanks, harbor, mountains, desserts and tennis courts.

### 4. Feature Extraction

The feature extraction is the important step in this project. Because based on the features extracted from the image, retrieval process has to be done. Here the two feature extraction algorithms are combined. They are Scale Invariant Feature Transform (SIFT) [1] and Gray Level Concurrence Matrix (GLCM) [3].

#### 4.1 SIFT Method

To aid the extraction of these features the SIFT [7] algorithm applies a 4 stage filtering approach:

##### a. Scale-Space Extrema Detection

This stage of the filtering attempts to identify those locations and scales that are identifiable from different views of the same object. This can be efficiently achieved using a "scale space" function. Further it has been shown under reasonable assumptions it must be based on the Gaussian function. The scale space is defined by the function:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

Where \* is the convolution operator,  $G(x, y, \sigma)$  is a variable-scale Gaussian and  $I(x, y)$  is the input image.

Various techniques can then be used to detect stable keypoint locations in the scale-space. Difference of Gaussians is one such technique, locating scale-space extrema,  $D(x, y, \sigma)$  by computing the difference between two images, one with scale  $k$  times the other.  $D(x, y, \sigma)$  is then given by:

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \quad (2)$$

To detect the local maxima and minima of  $D(x, y, \sigma)$  each point is compared with its 8 neighbours at the same scale, and its 9 neighbours up and down one scale. If this value is the minimum or maximum of all these points then this point is an extrema.

##### b. Keypoint Localisation

This stage attempts to eliminate more points from the list of keypoints by finding those that have low contrast or are poorly localised on an edge details. The location of extremum,  $z$ , is given by:

$$z = -\frac{\partial^2 D^{-1} \partial D}{\partial x^2 \partial x} \quad (3)$$

If the function value at  $z$  is below a threshold value then this point is excluded. This removes extrema with low contrast. To eliminate extrema based on poor localisation it is noted that in these cases there is a large principle curvature across the edge but a small curvature in the perpendicular direction in the difference of Gaussian function. If this difference is below the ratio of largest to smallest eigenvector, from the 2x2 Hessian matrix at the location and scale of the keypoint, the keypoint is rejected.

##### c. Orientation Assignment

This step aims to assign a consistent orientation to the keypoints based on local image properties. The keypoint descriptor, described below, can then be represented relative to this orientation, achieving invariance to rotation. The approach taken to find an orientation is:

- 1) Use the keypoints scale to select the Gaussian smoothed image  $L$ , from above
- 2) Compute gradient magnitude,  $m$

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2}$$

- 3) Compute orientation,  $\theta$

$$\Theta(x, y) = \tan^{-1}((L(x, y+1) - L(x, y-1)) / (L(x+1, y) - L(x-1, y)))$$

- 4) Form an orientation histogram from gradient orientations of sample points.
- 5) Locate the highest peak in the histogram. Use this peak and any other local peak within 80% of height of this peak to create a keypoint with that orientation.
- 6) Some points will be assigned multiple orientations.

- 7) Fit a parabola to the 3 histogram values closest to each peak to interpolate the peaks position.

#### d. Keypoint Descriptor

The local gradient data, used above, is also used to create keypoint descriptors. The gradient information is rotated to line up with the orientation of the keypoint and then weighted by a Gaussian with variance of  $1.5 * \text{keypoint scale}$ . This data is then used to create a set of histograms over a window centred on the keypoint.

Keypoint descriptors typically uses a set of 16 histograms, aligned in a  $4 \times 4$  grid, each with 8 orientation bins, one for each of the main compass directions and one for each of the mid-points of these directions. This results in a feature vector containing 128 elements.

#### 4.2 GLCM Method

The texture features are extracted according to the statistics of Gray-Level Co-occurrence Matrix (GLCM) [4]. Here GLCM is used to extract features which are all suitable for geographic image retrieval. Six textural parameters are considered to be the most relevant among the 14 originally proposed in : energy, contrast, variance, correlation, entropy and inverse difference moment. It first creates a co-occurrence matrix, also called as co-occurrence distribution. It is defined over an image to be the distribution of co-occurring values at a given offset. Particularly it represents the distance and angular spatial relationship over an image sub region of specific size.

1.'Contrast'-Returns a measure of the intensity contrast between a pixel and its neighbour over the whole image. Contrast is 0 for a constant image.

$$\text{Range} = [0 (\text{size}(\text{GLCM}, 1) - 1)^2]$$

2.'Correlation'- Returns a measure of how correlated a pixel is to its neighbor over the whole image.

Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.

$$\text{Range} = [-1 \ 1]$$

3.'Energy'- Returns the sum of squared elements in the GLCM. Energy is 1 for constant image

$$\text{Range} = [0 \ 1]$$

4.'Homogeneity'- Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM.

$$\text{Range} = [0 \ 1]$$

5.'Variance'- GLCM Variance in texture measures performs the same task as does the common descriptive statistic called variance. It relies on the mean, and the dispersion around the mean, of cell values within the GLCM. However, GLCM variance uses the GLCM, therefore it deals specifically with the dispersion around the mean of combinations of reference and neighbour pixels, so it is not the same as the simple variance of grey levels in the original image.

6.'Entropy'-Entropy(I) returns E, a scalar value representing the entropy of grayscale image I. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

### 5. Retrieval

Euclidean Distance[6]- Euclidean distance is computed between each database image & query image on feature vector to find set of images falling in the class of query image.

$$E.D = \sum_{i=1}^n \sqrt{(f_1 - f_2)^2}$$

Algorithm for feature extraction using SIFT-

- Feature Extraction
  1. Extract feature of the query image of user by selecting keypoints and store it in excel file.
  2. Extract features of all dataset images and store the feature vectors in excel file.
- Retrieval
  1. Calculate the euclidean distance between the query image feature vector and dataset images feature vector.
  2. Sort the dataset images in increasing order of euclidean distance .
  3. Retrieve the images by setting the threshold value.

Algorithm for feature extraction using GLCM-

- Feature Extraction
  1. Extract feature of the query image of user by selecting GLCM features such as contrast, correlation, energy, homogeneity and store it in excel file.
  2. Extract features of all dataset images and store the feature vectors in excel file.
- Retrieval
  1. Calculate the euclidean distance between the query image feature vector and dataset images feature vector.
  2. Sort the dataset images in increasing order of euclidean distance .
  3. Retrieve the images by setting the threshold value.

### 6. Results

The training data set consists of images of 23 LULC classes: agricultural, airplane, baseball diamond, beach, buildings, chaparral, dense residential, forest, freeway, golf course, intersection, medium density residential, mobile home park, overpass, parking lot, river, runway, sparse residential, storage tanks, harbor, mountains, deserts and tennis courts.

First step is preprocessing by Gaussian filter so as to remove noise.

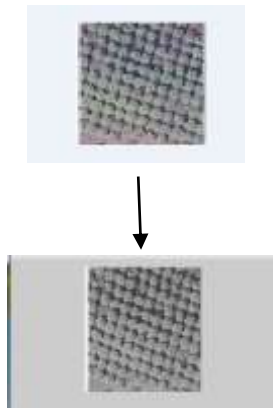


Figure2. Input Image and its preprocessed Image

After preprocessing SIFT keypoint detector will detect the keypoints from the input query image as shown in Figure 4.



Figure3. After finding keypoints

Once keypoints are known they will be compared against the dataset images keypoints and the similar images will be retrieved as output for a user query as shown in figure 5.



Figure4: Retrieved output which shows related images to the input image.

In GLCM approaches, it creates the cooccurrence Matrix[8] also called as gray-co matrix. It first initially assigns zero value to matrix. After the first iteration step, it assigns the values in the matrix. Finally it fills the full values in that matrix. The GLCM is used to extract six features[2]. They are energy, contrast, variance, correlation, entropy and inverse difference moment. The values of each get stored in each variables starting from v1 to v6.

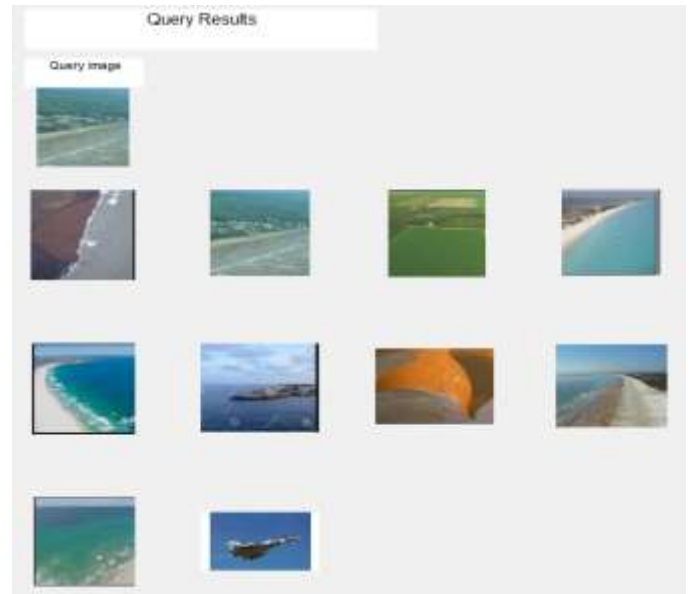


Figure5: The input image and corresponded retrieved seashore images output.

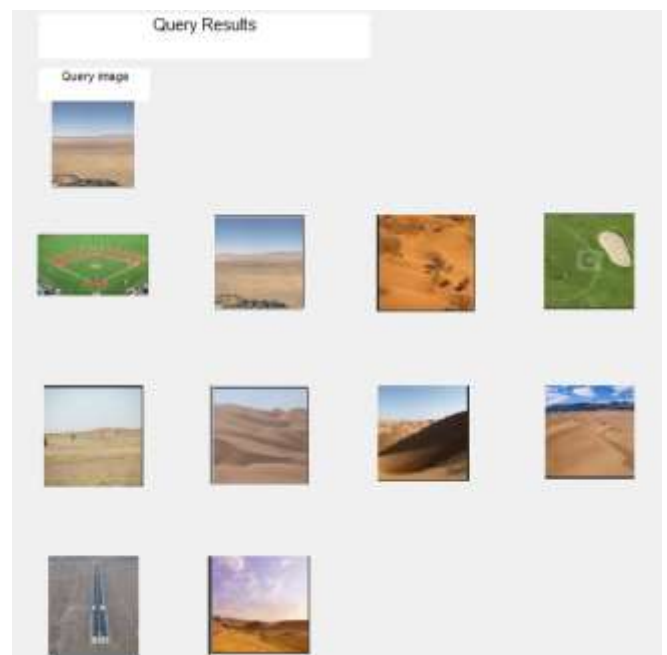


Figure6: The input image and corresponded retrieved dessert output.

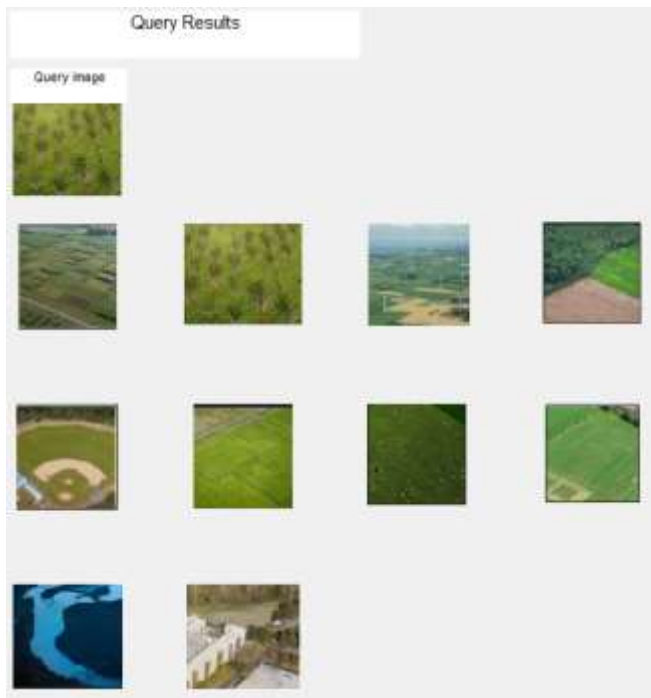


Figure7: The input image and corresponded retrieved agricultural fields output.

## 7. Conclusion

This paper presents an approach for geographic image retrieval. The paper is using two feature extraction techniques (Gray Level Concurrence Matrix, Scale Invariant Feature Transform) yields an accurate retrieval result as more features are extracted to provide the better retrieval result. This project is used in remote sensing, to locate the similar Land Use Land Cover Areas.

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## Author Profile



**Preeti Yadav** received the B.E degree in Computer Engineering from MGM Engineering College in 2008 to 2012. Now pursuing ME. from Thadomal Shahani Engineering College since 2013 till 2015.