INTERNATIONAL JOURNAL OF RESEARCH IN COMPUTER APPLICATIONS AND ROBOTICS
ISSN 2320-7345

OBJECT IDENTIFICATION METHOD USING MAXIMUM LIKELIHOOD ALGORITHM FROM GOOGLE MAP

Parivallal R[1], Nagarajan B[2], Nirmala Devi[3]

[1] *Assistant Professor, parivallalr@bitsathy.ac.in*
[2] *Director (MCA), nagarajanb@bitsathy.ac.in*
[3] *Final Year MCA*
Author Correspondence: Department of Computer Applications, Bannari Amman Institute of Technology, Sathyamangalam, Tamil Nadu, India – 638401.
Email address: parivallalr@bitsathy.ac.in

Abstract

The main aim of this paper is to extract buildings automatically from high resolution satellite image, and count the number of buildings from the satellite image. For extract the buildings the authors classify the image using maximum likelihood algorithm. To classify the image using training data and choose the training pixels, then count the number of extracted buildings from the classified image using MATLAB. Using this technique, we get the good result from the Google satellite maps.

Keywords*:* Building Extraction, Maximum Likelihood, Classification, Google Maps.

1. Introduction

Satellite images offer valuable information to researchers. Google map provides high-resolution aerial or satellite images for most urban areas of the world. The Google map does not allow detecting the spatial objects and counting the number of detecting objects. Therefore, mostly we focused on extracting the number of spatial objects. As the advent of very high resolution (VHR) satellite imagery (such as Ikonos and Quickbird), it became possible to observe these objects [1]. Aside from region properties, extracting spatial objects in VHR satellite images may help researchers in various ways, such as automated map making [2].

Among different spatial objects, buildings play an important role. Therefore, the detection of buildings in HR (high-resolution) satellite images requires a specific consideration. Also building extraction is one of the main procedures used in updating digital maps [3]. Building extraction is a difficult task, because the building doesn't follow a specific pattern and the individual building covers a very small area on the ground. In addition, the reflectance of buildings and roads are almost similar in satellite images which results in error in digital classification. In that case, differentiation between buildings and road becomes very difficult. Because of this reason, some additional features (like area, shape etc.) are also required for increasing the accuracy of extracted buildings from satellite images.

Unfortunately, it is still tedious for a human expert to manually label buildings in a given satellite image. One main reason is the total number of objects in the scene. The other reason is the resolution of the satellite image. Although the resolution of the satellite imagery has reached an acceptable level, it is still not possible for a human expert to extract information from it in a robust manner [4] [5]. To solve this problem, we introduced automated urban-area- and building-detection methods using high resolution satellite and aerial images.

Two main groups of building detection techniques using high resolution imagery can be considered [6] as low-level vision and high-level vision techniques. Low-level vision techniques are mainly based on edge detection and extraction from images. High-level vision techniques try to imitate the human cognition process .Pattern and object recognition, and image classifications are common high-level vision techniques [7]. However, many of the low-level vision techniques are strongly restricted, previous research defined a series of rules that buildings should accomplish such as rectangular shape, flat roofs or specific spectral responses [8].

A lot of work has been done on building extraction from high resolution satellite images. V. Karathanassi and D. Rokos introduced a texture-based classification method for classifying built areas according to their density [9].Luis A. Ruiz and Jorge A.Recio [10] provides automatic building detection approaches combining high-resolution images and LiDAR data. Tian J and Wang introduced urban building boundary extraction from IKONOS imagery [11]. Benediktsson et al. [12] used mathematical morphological operations to extract structural information to detect the urban area in satellite images. Tarantino and Figorito [13] used a decision making strategy to extract buildings from true color stereo aerial images.M.Roux [14] provides feature matching for building extraction from multiple views.Grigillo D [15] provides automatic building extraction from IKONOS images in suburban areas. Segl K and Kaufmann detected the small objects from high-resolution pan images [16].

In Section II, the study area will be discussed. In Section III the methodology will be discussed. In Section IV deals with the results and In Section V, conclusion will be discussed.

2. Study area

In this paper the study area was located in Sathyamangalam (Urban area) covering approximately 675 km2 extracted from Google maps within latitude11.50549 E to11.50654 E and longitude 77.23840 N to 77.24013 N (see Fig 1). Because, urban area characterized by higher population density and very attached buildings. So that we have taken urban region image.

Figure 1: Original image (Urban)

3. Methodology

3.1 Object-based classification

In this object-based classification technique, we follows the standard scheme of object-based image classification (Fig: 2) Segmentation before classification by using the ENVI EX tool [17]. Segmentation and classification by using Maximum Likelihood Algorithm. Maximum likelihood, also called the maximum likelihood method, is the procedure of finding the value of one or more parameters for a given statistic which makes the known likelihood distribution a maximum.

Vol.2 Issue.2, Pg.: 153-159
February 2014

Figure 2 (a) : Segmented image (b) Merged image

Figure 3: Classified image

This algorithm allowing different sets of classes to be classified using different spatial features in a hierarchical format. However, there are still significant classification errors in dense urban areas. In the present urban land cover map, all man-made structures are classified as either *Road* or *Building*. In suburban areas, this scheme is appropriate as residential homes and streets dominate the landscape.

However, in more dense urban areas, there are significant amounts of non-road impervious surface land cover, such as parking lots and large sidewalks, and it is very desirable to differentiate between these surfaces and buildings.

Maximum Likelihood (ML) [18] is a supervised classification method derived from the Bayes theorem, which states that the a posteriori distribution P(i|ω), i.e., the probability that a pixel with feature vector ω belongs to class i, is given by:

$$P(i\,|\,\omega) = \frac{P(\omega\,|\,i)\,P(i)}{P(\omega)} \quad (1)$$

where P(ω|i) is the likelihood function, P(i) is the a priori information, i.e., the

probability that class i occurs in the study area and P(ω) is the probability that ω is observed, which can be written as:

$$P(\omega) = \sum_{i=1}^{M} P(\omega\,|\,i)P(i) \quad (2)$$

where M is the number of classes. P(ω) is often treated as a normalization constant to ensure $\sum P(i\,|\,\omega)$ sums to 1. Pixel **x** is assigned to class i by the rule:

$$\mathbf{x} \in i \quad \text{if } P(i|\,\omega) > P(j|\,\omega) \quad \text{for all } j \neq i \quad (3)$$

ML often assumes that the distribution of the data within a given class i obeys a multivariate Gaussian distribution. It is then convenient to define the log likelihood (or discriminant function):

$$gi(\omega)=\ln P(\omega|i)=-1/2(\omega-\mu i)^t\, Ci^{-1}(\omega-\mu i)-N/2\ln(2\pi)-1/2\ln(|Ci|) \tag{4}$$

Since log is a monotonic function, Equation (3) is equivalent to:

$$\mathbf{x}\in i \text{ if } g_i(\omega) > g_j(\omega) \text{ for all } j\neq i . \tag{5}$$

Each pixel is assigned to the class with the highest likelihood or labeled as unclassified if the probability values are all below a threshold set by the user [9]. The general procedures in ML are as follows:

1. The number of land cover types within the study area is determined.
2. The training pixels for each of the desired classes are chosen using land cover information for the study area. For this purpose, the Jeffries-Matusita (JM) distance can be used to measure class separability of the chosen training pixels.

   For normally distributed classes, the JM separability measure for two classes, J_{ij}, is defined as follows [4]:

$$Jij = \sqrt{2(1-e^{-\alpha})} \tag{6}$$

where α is the Bhattacharyya distance and is given by [19]:

$$\alpha = 1/8(\mu i - \mu j)^t \{(Ci + Cj) / 2\}^{-1} (\mu i - \mu j) + 1/2\ln (|Ci + Cj) / 2| / \sqrt{|\, Ci \,||\, Cj\, |}) \tag{7}$$

J_{ij} ranges from 0 to 2.0, where $J_{ij} > 1.9$ indicates good separability of classes, moderate separability for $1.0 \leq J_{ij} \leq 1.9$ and poor separability for $J_{ij} < 1.0$ [20].

3. The training pixels are then used to estimate the mean vector and covariance matrix of each class.
4. Finally, every pixel in the image is classified into one of the desired land cover types or labelled as unknown.

In ML classification, each class is enclosed in a region in high-resolution space where its discriminant function is larger than that of all other classes. These class regions are separated by decision boundaries, where, the decision boundary between class i and j occurs when:

$$g_i(\omega) = g_j(\omega) \tag{8}$$

For multivariate normal distributions, this becomes:

$$-1/2(\omega - \mu i)^t\, Ci^{-1}(\omega - \mu i)-N/2\ln(2\pi)-1/2\ln(|Ci|)-(-1/2(\omega - \mu j)^t\, Cj^{-1}(\omega - \mu j)-N/2\ln(2\pi)-1/2\ln(|Cj|))=0 \tag{9}$$

which can be written as:

$$-(\omega - \mu i)^t\, Ci^{-1}(\omega - \mu i)-\ln(|Ci|)+(\omega - \mu j)^t\, Cj^{-1}(\omega - \mu j)-\ln(|Cj|)=0 \tag{10}$$

This is a quadratic function in N dimensions. Hence, if we consider only two classes, the decision boundaries are conic sections (i.e. parabolas, circles, ellipses or hyperbolas. Google maps imagery has very low contrast, and it was found that if the image is histogram (Fig: 3) equalized before classification, the classification results were greatly improved. While many of the road and impervious surface regions in the image are broken into multiple segments, the classification successfully segments most of the buildings in the image as single segments. From this classification image it is then possible to use an object-based classification approach to differentiate between the *Building* and *Impervious Surface* classes.

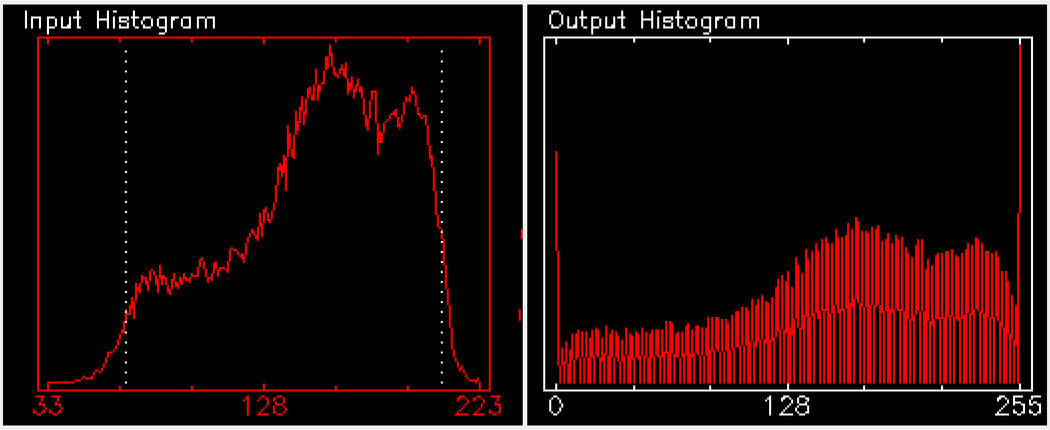

Figure 3: Histogram for urban image

3.2 Identification of spatial objects:

In this technique we count the number of spatial objects by using classified image. We extract the classified image which is shape (.shp) file (Fig: 3(a)) in format. We have taken the shape file then read the image and convert the shape file into binary image (Fig: 3(b)).

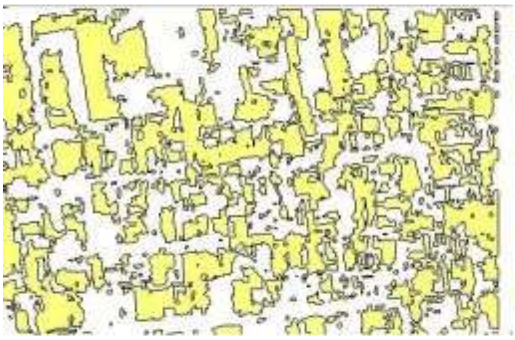

Figure: 3 (a) shape (.shp) image

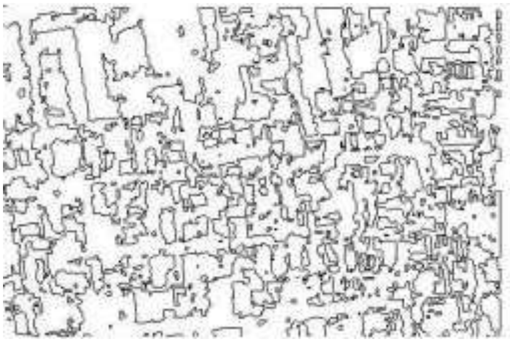

Figure: 3 (b) binary image

4. Results

The method described above automatically extracts buildings from satellite images. The original Google image and the extracted buildings from that image are shown in (Fig: 4). There are 368 buildings present in the original Google image. After applying the proposed method, maximum buildings are extracted. After comparing the manually digitized buildings and the extracted buildings, we found that few patches are wrongly identified as buildings.

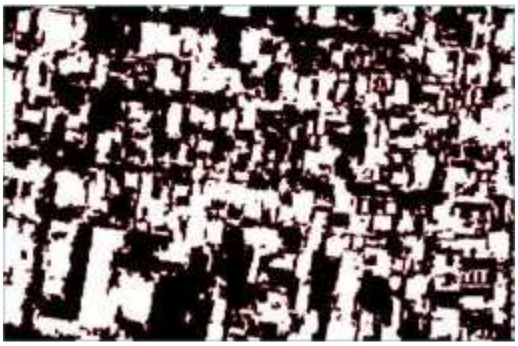

Figure 4: Extracted urban image

5. Conclusion:

This paper presents an object-based detection in high-resolution imagery such as Google maps. We have taken the urban image to this research it produces the good result. The maximum buildings are detected and counted. In future we apply this technique to the various applications like urban planning, rural development.

REFERENCES

[1] J. A. Benediktsson, M. Pesaresi and K. Amason, 2003, "Classification and feature extraction for remote sensing images from urban areas based on morphological transformations," IEEE Transactions on Geoscience and Remote Sensing, vol. 41, pp. 1940-1949, 2003.

[2] A. K. Shackelford and C. H. Davis, 2003,"A combined fuzzy pixel-based and object-based approach for classification of high-resolution multispectral data over urban areas," Geoscience and Remote Sensing, IEEE Transactions on, vol. 41, pp. 2354-2363, 2003.

[3] E. Tarantino and B. Figorito, "Extracting Buildings from True Color Stereo Aerial Images Using a Decision Making Strategy," Remote Sensing, vol. 3, pp. 1553-1567, 2011.

[4]. Couloigner and T. Ranchin, “Mapping of urban areas: A multiresolution modeling approach for semi-automatic extraction of streets,” Photogramm. Eng. Remote Sens., vol. 66, no. 7, pp. 867–874, July 2000.

[5] O. Benarchid, N. Raissouni, S. El Adib, A. Abbous, A. Azyat, N. Ben Achhab, M. Lahraoua, and A. Chahboun, “Building Extraction using Object-Based Classification and Shadow Information in Very High Resolution Multispectral Images, a Case Study: Tetuan, Morocco, Canadian Journal on Image Processing and Computer Vision Vol. 4 No. 1, January 2013.

[6]A.K. Shackelford, C.H. Davis, and X. Wang, "Automated 2-D Building Footprint Extraction from High-Resolution Satellite Multispectral Imagery," in IGARSS '04, pp. 1996-1999, 2004.

[7] T. Hermosilla, L.A. Ruiz, J.A. Recio, and J. Estornell, "Evaluation of Automatic Building Detection Approaches Combining High Resolution Images and LiDAR Data ," Remote Sensing, vol. 3, pp. 1188-1210, 2011.

[8] R.B. Irvin and D.M. McKeown, Jr., "Methods for Exploiting the Relationship between Buildings and their Shadows in Aerial Imagery ," IEEE Trans. Syst. Man Cybern, vol. 19, pp. 1564-1575, 1989.

[9] V. Karathanassi, C. Iossifidis, and D. Rokos, “A texture-based classification method for classifying built areas according to their density,” Int. J. Remote Sens., vol. 21, no. 9, pp. 1807–1823, Jun. 2000.

[10] Evaluation of Automatic Building Detection Approaches Combining High Resolution Images and LiDAR Data Txomin Hermosilla *, Luis A. Ruiz, Jorge A. Recio and Javier Estornell

[11]Tian, J.; Wang, J.; Shi, P. Urban Building Boundary Extraction from IKONOS Imagery. In Proceedings of The 25th Canadian Symposium on Remote Sensing, Montreal, QC, Canada, 14–16 October 2003; p. 6.

[12] J. A. Benediktsson, M. Pesaresi, and K. Arnason, “Classification and feature extraction for remote sensing images from urban areas based on morphological transformations,” IEEE Trans. Geosci. Remote Sens., vol. 41, no. 9, pp. 1940–1949, Sep. 2003.

[13] E. Tarantino and B. Figorito, "Extracting Buildings from True Color Stereo Aerial Images Using a Decision Making Strategy," Remote Sensing, vol. 3, pp. 1553-1567, 2011.

Vol.2 Issue.2, Pg.: 153-159
February 2014

[14] M. Roux and D. McKeown, "Feature Matching for Building Extraction from Multiple Views," In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp. 46-53, Seattle, WA., June 1994.

[15] D. Grigillo, M.K. Fras, and D. Petrovic, "Automated Building Extraction from IKONOS Images in Suburban Areas," Remote Sensing, vol. 33, pp. 5149-5170, 2012.

[16] K. Segl and H. Kaufmann, 2001,"Detection of small objects from high-resolution panchromatic satellite imagery based on supervised image segmentation," Geoscience and Remote Sensing, IEEE Transactions on, vol. 39, pp. 2080-2083, 2001.

[17] "Imagine Objective, User's Guide 2011," 2008.

[18] Asmala Ahmad, "Analysis of Maximum Likelihood Classification on Multispectral Data", Applied Mathematical Sciences, Vol. 6, 2012, no. 129, 6425 – 6436

[19] J.A. Richards, Remote sensing digital image analysis: An introduction. Springer- Verlag, Berlin, Germany, 1999.

[20] ENVI, User's guide, Research Systems Inc., USA, 2006.

A Brief Author Biography

Parivallal R received M.C.A. and M.Phil. Degree in the year 1997 and 2005 respectively. He is having 15 years of teaching experience in college. His area of interest is Data Mining and Image Processing. He has presented more than 10 technical papers in various Seminars / Conferences. He is a member of Indian Society for Technical Education (ISTE). He is also act as a Principal Investigator in DST – NRDMS Funded Research Project.

Dr. B. Nagarajan received the Doctorate degree from Anna University, Chennai in the year 2012. He is having more than 15 years of Experience and currently working as a Director, Department of Computer Applications, Bannari Amman Institute of Technology, Sathyamangalam, Tamil Nadu, India. His area of interest includes Artificial intelligence, Neural Networks, Image Processing. He has completed two Funded Research Projects in DRDO and AICTE. He is a Life member of Computer Society of India (CSI) and a Life member of Indian Society for Technical Education (ISTE).