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SUPERVISED CLASSIFICATION METHODS FOR OBJECT IDENTIFICATION USING GOOGLE MAP IMAGE

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ABSTRACT

Recently Government and private agencies use Google map images for a wide range of applications like urban planning, travel planning etc. Image classification is an important application for remote sensing. A few number of image classification algorithms have proved good precision in classifying remote sensing data. Due to the increasing spatiotemporal dimensions of the remote sensing data, traditional classification algorithms have exposed weaknesses necessitating further research in the field of remote sensing image classification. So an efficient classifier is needed to classify the Google map imageries to extract information. In this paper we compare the different classification methods and their performances. It is found that our enhanced method of classifier performed the best classification.

I. 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 provide detecting the spatial objects and counting the number of detected 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.

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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].

Image classification can be viewed as a joint venture of both image processing and classification techniques. Generally, image classification, in the field of remote sensing is the process of assigning pixels or the basic units of an image to classes. It is likely to assemble groups of identical pixels found in remotely sensed data into classes that match the informational categories of user interest by comparing pixels to one another and to those of known identity.

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. In some cases, the classification itself may form the entity of the analysis and serve as the ultimate product. In other cases, the classification can serve only as an intermediate step in more intricate analyses, such as land degradation studies, process studies, landscape modeling, coastalzone management, resource management and other environment monitoring applications. As a result, image classification has emerged as a significant tool for investigating digital images. Moreover, the selection of the appropriate classification technique to be employed can have a considerable up shot on the results of whether the classification is used as an ultimate product or as one of numerous analytical procedures applied for deriving information from an image for additional analyses [25].

The performance [22] of the classifiers depends upon the data. So a better understanding of data is necessary for further advances. Such an understanding is not possible in the traditional theoretical studies. Comparative studies of classifiers that relate their performances to data characteristics have received attention only recently. Successful classification requires experience and experimentation. The analyst must select a classification method that will best accomplish a specific task. At present it is not possible to state which classifier is best for all situation as the characteristics of each image and the circumstances for each study vary so greatly.

II. SUPERVISED CLASSIFICATION

Image classification is the process of assigning pixels or the basic units of an image to classes. It is likely to assemble groups of identical pixels found, into classes that match the informational categories of user interest by comparing pixels to one another and to

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The remote sensing literature presents with a number of supervised methods that have been developed to tackle the multispectral data classification problem. The statistical method employed for the earlier studies of land-cover classification is the maximum likelihood classifier. In recent times, various studies have applied artificial intelligence techniques as substitutes to remotely-sensed image classification applications. In addition, diverse ensemble classification method has been proposed to significantly improve classification accuracy [22]. Scientists and practitioners have made great efforts in developing efficient classification approaches and techniques for improving classification accuracy.The quality of a supervised classification [23] depends on the quality of the training sites. All the supervised classifications usually have a sequence of operations that must be followed. 1. Defining of the Training Sites.2. Extraction of Signatures. 3. Classification of theImage. The training sites are done with digitized features. Usually two or three training sites are selected.

The more training site is selected, the better results canbe gained. This procedure assures both the accuracy of classification and the true interpretation of the results.After the training site areas are digitized then the statistical characterizations of the information are created. These are called signatures. Finally the classification methods are applied.

III. STUDY AREA

In this paper the study area was located in Sathyamangalam (Rural area) covering approximately 675 km2 extracted from Google maps (see Fig 1). Rural area characterized by population density and buildings.

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Figure 1: Rural Area Image from Google Map

IV. IMPLEMENTATION

The main aim of the study is to evaluate the performance of the different classification algorithms using the Google Map.

4.1. MINIMUM DISTANCE TECHNIQUE

It is based on the minimum distance decision rule that calculates the distance between the measurement vector for the candidate pixel and the mean vector for each sample. Then it assigns the candidate pixel to the class having the minimum spectral distance. The classified image is :

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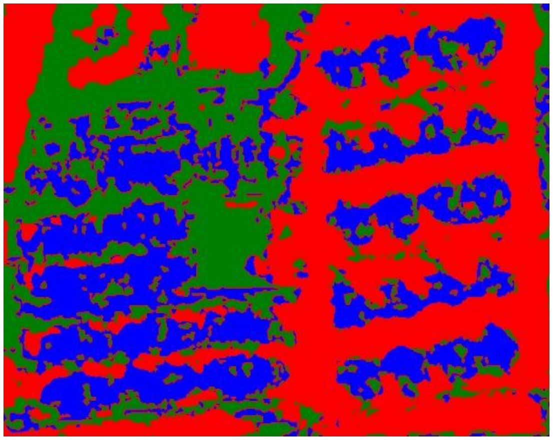
4.2. MAXIMUM LIKELIHOOD

This Classification uses the training data by means of estimating means and variances of the classes, which are used to estimate probabilities and also consider the variability of brightness values in each class. This classifier is based on Bayesian probability theory. It is the most powerful classification methods when accurate training data is provided and one of the most widely used algorithm. The classified image is shown as follows:



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4.3. ARTIFICIAL NEURAL NETWORK (ANN) CLASSIFIER

A multi-layered feed-forward ANN [16] is used to perform a non-linear classification. This model consists of one input layer, at least one hidden layer and one output layer and uses standard back propagation for supervised learning. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back propagated through the network and weight adjustment is made using a recursive method.

4.4. MAHALANOBIS DISTANCE

Mahalanobis distance classification is similar to minimum distance classification except that the covariance matrix is used. The Mahalanobis distance algorithm assumes that the histograms of the bands have normal distributions.

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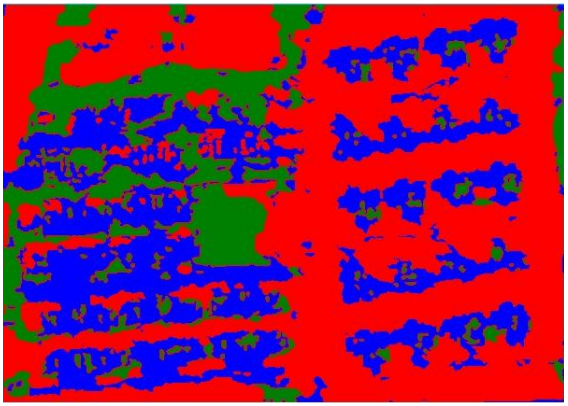
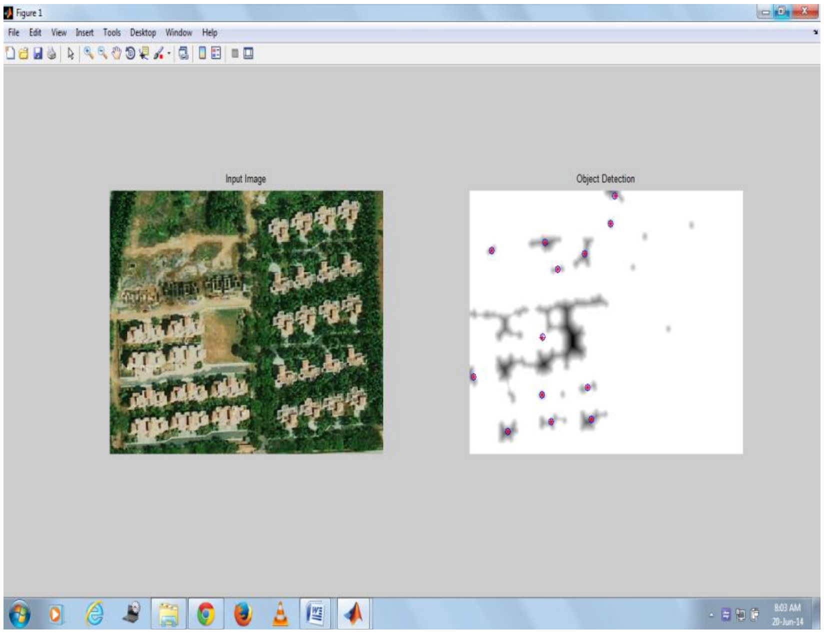


4.5. PROPOSED METHOD

In this proposed method applied Pre-processing of input image and Segmentation by Threshold Segmentation, Watershed Segmentation and Morphological operations on given Google map Image. The extracted building regions from the given image are highlighted in the final output of the Google image.



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V. PERFORMANCE AND CONCLUSION

A study of the performance of various classifiers mentioned above based on the overall accuracy, kappa coefficient is made. It is observed that our proposed classification method is determined to be the most accurate. One of the reasons is it filters out shadows and also it classifies the highly varied clusters. The output of the classification is shown in the above figures. Overall, the proposed classifier shows the highest accuracy assessment for this particular area.

In this paper we have compared the performance of various classifiers and found that the proposed classifier outperforms even advanced classifiers. The algorithm classified the number of classes and more land cover and landuse. This would save more human resources, time and fund.

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