Semi-Automatic Extraction of Large and Moderate Buildings from Very High-Resolution Satellite Imagery using Active Contour Model

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CERTIFICATE

It is certified that the work contained in this thesis, titled "**Semi-Automatic Extraction of Large and Moderate Buildings from Very High-Resolution Satellite Imagery using Active Contour Model**" by **Sandeep Kumar Bypina**, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date

Adviser: Prof. K. S. Rajan

To My Family

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1. Prof. K.S.Rajan, for the invaluable guidance, support and patience.

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Abstract

The satellite imagery has different types of objects like buildings, vegetation, lakes, roads, grounds etc. Each type of object has unique characteristics like texture, colour, spatial arrangement etc that differentiates them from other types of objects. Using a single method to extract all these types of objects might not be logical. Detecting buildings from satellite imagery is of major importance for supporting government related activities and a great support in crisis situations for disaster management.

This work presents a new way of automating the extraction of buildings from high resolution satellite images using Object Based Image Analysis (OBIA). The proposed algorithm utilizes an active contour model called Chan-Vese segmentation that is capable of accurately locating various objects in the image. Additionally, to ensure accuracy, the algorithm employs Normalized Difference Vegetation Index (NDVI) mask to remove vegetation areas.

Moreover, these detected objects pass through a careful filtering process based on regional characteristics like minimum area and object width thereby improving the precision of the identified structures. The correctness of results is confirmed by conducting rigorous quantitative assessments for validation purposes. This means that not only does this comprehensive approach guarantee error-free building identification but also suggests a strong framework for automatic building extraction from high resolution satellite imagery.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Automatic Building extraction is very useful for various applications such as Urban Planning and Disaster Management. In Practice, building extraction from satellite imagery is very complex because buildings have various forms and have different roof compositions. Over the past few years, lot of efforts have been made to automatically extract buildings from digital imagery. However, the existing automatic building extraction methods are still limited to specific applications[6]. In the absence of automated techniques, semi-automatic techniques seems to be an alternative solution[4],[5],[7],[8].

With the advent of high-resolution satellite imagery, there is much higher possibility of effective techniques that extracts buildings in a settlement. However, the high-resolution images can't be processed using the basic pixel-wise interpretation methods because it suffers from ‘‘salt-and-pepper’’ phenomenon, which is attributed to the spectral heterogeneity and spatial variance[8],[9]. The object-based image analysis (OBIA) is advantageous to deal with objects that are composed of homogeneous pixels.

1.1 Related Works

Though a lot of research has gone into automatically extracting buildings from high-resolution satellite imagery, the existing techniques are still performing at basic level and are limited to specific applications. In general, building extraction from satellite imagery consists of two main tasks: building detection and building reconstruction [12]. However building extraction tasks may differ depending on the use of models. For instance, the use of geometrical representation with rectangular models [13], use of lines, points and regions to describe building outlines[16], use of multiple images [14] and polyhedral shapes [15].

The main difficulty that the automated techniques face is due to the image variation in terms of type, scale and level of detail[17]. Secondly, the automatic extraction of semantic information using computer systems is complicated; most of the existing algorithms tend to fail whenever a new situation in image space is encountered or when objects are close to each other [18],[3]. This implies that, to have accurate results using automatic techniques, the buildings should have minimum gap which is not possible in real world. Haverkamp (2003)[5] used linking edge chains to extract rectilinear buildings from IKONOS images. Mayunga et al. (2005)[4] proposed an improvised active contour model(snakes) with radial casting initialization on Quickbird imagery. Based on the facts that radial casting initialization of active contour model depends on building complexity, Theng (2006)[19] proposed a circular casting initialization algorithm with the existing snake energy function.

Numerous efforts have been made in developing OBIA applications focusing on the identification and classification of urban features. Most notably, Thomas et al. (2003)[20] assessed the accuracy of three different methods for extracting urban land-cover/land-use information from high-resolution imagery for the city of Scottsdale, Arizona, for storm-water runoff estimation. Similarly, Carleer et al. (2005)[21] compared four segmentation algorithms from the two main groups of segmentation algorithms (boundary-based and region-based), applied on very high spatial resolution images for different landscapes, and differentiated urban areas into residential, urban administrative zones and urban dwelling zones. Turker and Sumer (2008)[22] detected damaged buildings from watershed segmentation of post-event aerial images utilizing the relationship between the buildings and their shadows. Tomljenovic et al., (2014)[23] developed an Object-Based Image Analysis (OBIA) approach for building extraction starting from LiDAR point data only.

In this work, we start with the application of watershed segmentation in detecting objects from a spatial image. Later, a simple yet effective approach is proposed, which extracts buildings of all kinds from high-resolution satellite imagery using Chan-Vese segmentation and OBIA techniques.

Chapter 2

Watershed Segmentation

Object Based Image Analysis (OBIA) applied to satellite imagery, often referred to as GEOBIA (Geographic Object Based Image Analysis), operates on two fundamental principles:

1.Segmentation: The process entails breaking down the satellite image into distinct objects that represent various land-based features. This segmentation step is crucial as it forms the foundation for subsequent analysis and interpretation.

2.Classification: Once the segmentation is complete, the identified objects are classified based on a multitude of criteria, including their shape, size, spatial relationships, and spectral properties. This classification step enables the extraction of meaningful information from the imagery, facilitating the identification and characterization of different features and structures with precision.

By adhering to these principles, GEOBIA offers a systematic and robust approach to analyzing satellite imagery, providing valuable insights into the landscape and enabling diverse applications across various domains such as urban planning, environmental monitoring, and land management.

2.1 Watershed Segmentation

The watershed algorithm, a fundamental technique in image processing, conceptualizes the image as a topographic landscape, wherein dark foreground objects represent catchment basins and light background objects act as dividing dams. Initially, our exploration focused on implementing the watershed algorithm on grayscale images. To enhance edge detection crucial for segmentation, we employed the Sobel operator to derive a gradient image, leveraging its capability to capture detailed edge information. Subsequently, minima within this gradient image were identified within various neighborhoods determined by AxB size masks, initiating region growing or "flooding" from these minima. This novel approach, termed the Minima Growing Watershed Algorithm, adhered to specific stopping criteria:

a) Region growth halts upon contact with neighboring regions.

b) Pixel inclusion in the region is contingent upon satisfying a predefined threshold criterion.

Chapter 2

For initial experimentation, we applied the Minima Growing Watershed Algorithm to a standard grayscale image (Fig.2.1). The resultant gradient image obtained through the Sobel operator (Fig.2.2) was followed by minima identification using a 13x13 mask (Fig.2.3), culminating in region growing with a threshold of 10 (Fig.2.4). Subsequently, our focus shifted to real-world spatial imagery (Fig.2.5), prompting exploration of several approaches:

1. Application of the Minima Growing Watershed Algorithm individually on each color band (R, G, B), with the outputs merged to form a color display. However, the results obtained were deemed unsatisfactory.

2. Conversion of the colored image to grayscale, followed by derivation of the gradient image (Fig.2.6). Minima were directly identified on this grayscale gradient image, with subsequent region growing incorporating threshold verification using the mentioned criteria (Equation 1). This approach yielded a marginally improved output (Fig.2.7).

$$MAX(|Rx - Ry|, |Gx - Gy|, |Bx - By|) < Threshold \qquad \text{- Equation 1}$$

Figure 2.1. Original Bicycle Image

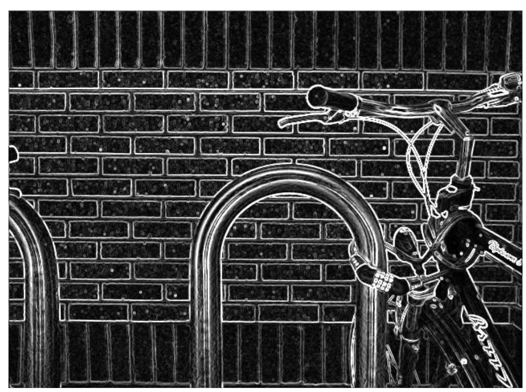

Figure 2.2. Gradient Image with Sobel Operator

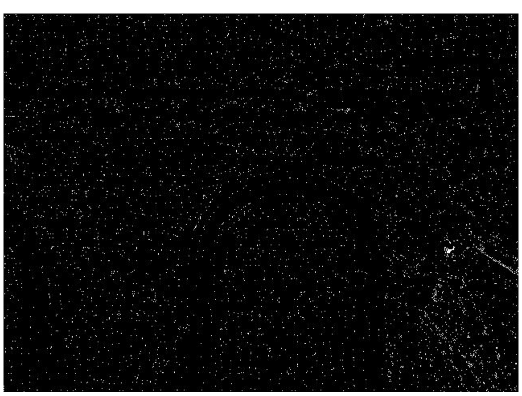

Figure 2.3. Minima image with 13x13 mask

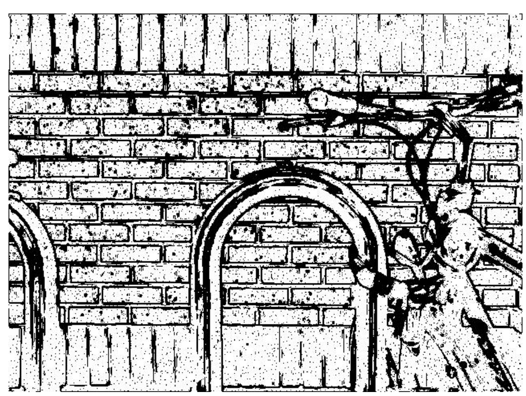

Figure 2.4. Region grown image with threshold 10

Chapter 2

Upon Observing the aforementioned approaches, we identified a directional bias in processing. Specifically, processing from left to right predisposed left pixels to be processed first, potentially leading to biased merging with minima. To rectify this issue, we sought to mitigate directional biases by implementing the Priority Queue method to simulate the watershed algorithm.

2.2 Priority Queue or Ordered Queue

The Priority Queue, or Ordered Queue, is structured as a series of simple queues, with each queue assigned a priority level corresponding to intensity values. Points are dequeued solely from the queue with the highest priority. If extraction from the current queue fails, the queue is suppressed, and the next lower-priority queue is accessed. Notably, if a high-priority point arrives after the corresponding queue has been suppressed, it is placed at the end of the current queue of highest priority. This algorithm is primarily characterized by two steps:

1. **Initialization:** A set of markers serving as flood sources is defined, each identified by labels. Each region retains the label of the marker satisfying a threshold criterion based on the maximum intensity difference among color channels.

2. **Growing of Markers:** For each point extracted from the ordered queue:
   a) If the point neighbors only one labeled region, it is incorporated into that region, and its unlabeled neighbors outside the queue are added to the queue with the same priority.
   b) If the point neighbors two regions with different labels, it is labeled as a boundary point characterizing the frontier.

The resulting output image after applying this methodology to spatial imagery is depicted in fig.2.8. This output demonstrates fewer objects compared to the oversampled Minima Growing watershed output, albeit with a higher tendency for objects to be classified as multiple entities due to the reduced segmentation granularity.

Subsequently, we applied the priority queues watershed algorithm following image preprocessing with low-pass (fig.2.10) and high-pass (fig.2.9) filters, enabling a comparative analysis. The high-pass output exhibited enhanced segmentation owing to edge enhancement, whereas the low-pass output depicted merged objects attributed to smoothed edges.

Figure 2.5. Satellite Image

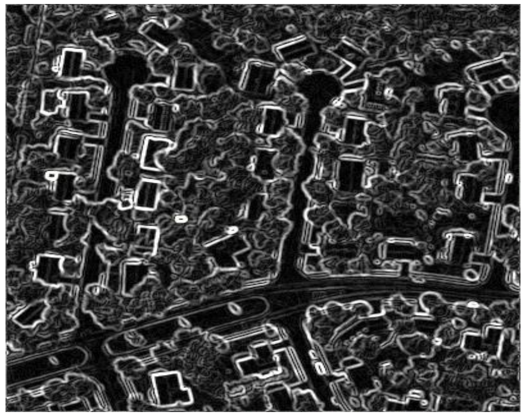

Figure 2.6. Gradient of Satellite Image

Figure 2.7. Output of Minima Growing Watershed algorithm on Satellite Image

Figure 2.8. Output of Priority Queue Watershed algorithm on Satellite Image

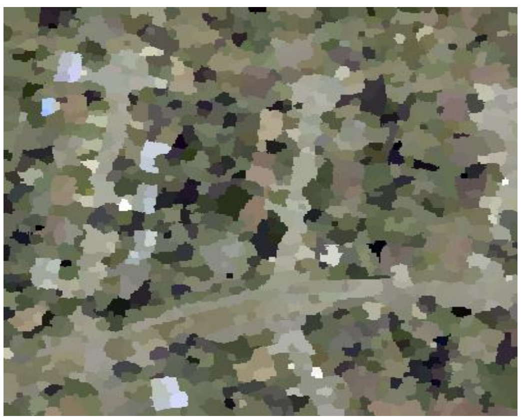

Figure 2.9. Output of Priority Queue after High pass filter on Satellite Image

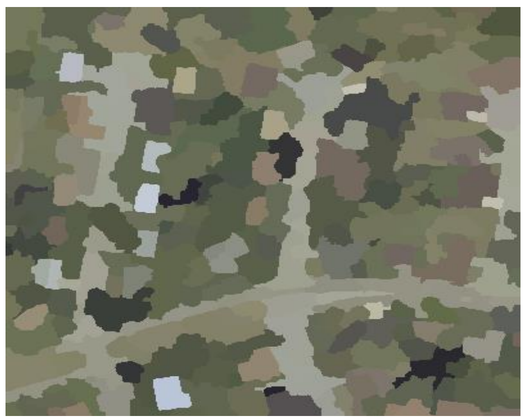

Figure 2.10. Output of Priority Queue after Low pass filter on Satellite Image

Chapter 2

2.3 Challenges in Watershed Segmentation

In exploring the watershed algorithm, we encountered several challenges inherent to its application, particularly in the context of spatial imagery:

1. **Over-Segmentation in Noisy Images:** One prominent challenge pertains to the algorithm's propensity for over-segmentation, especially in images characterized by high levels of noise. Spatial imagery, in particular, tends to exhibit elevated noise levels due to various factors such as sensor limitations and atmospheric interference. The presence of such noise can lead to the erroneous delineation of boundaries, resulting in an excessive number of segmented regions.

2. **Trade-off Between Noise Reduction and Edge Preservation:** Attempting to address noise-related issues by employing image smoothing techniques introduces a trade-off between noise reduction and edge preservation. Smoothing operations, such as Gaussian filtering, effectively diminish noise but inadvertently blur image features, including edges. Consequently, this blurring phenomenon can lead to the merging of adjacent objects during segmentation, undermining the algorithm's ability to accurately delineate boundaries.

Chapter 3

Building Detection Using Chan-Vese Segmentation

Automatic building extraction is an active research in remote sensing recently. It has been going on for more than 20 years but the automated extractions still encounter problems due to image resolution, variation and level of details. Mayunga et al. (2005) developed an improved snake model. However their radial casting encounters difficulties in initializing the snake model. This research discusses the development of an approach based on Chan-Vese Segmentation Method which uses active contour model to extract the objects from an image.

3.1 Chan-Vese Segmentation

The Chan-Vese segmentation[1] model is an active contour model based on Mumford-Shah segmentation techniques[2] and level sets. The basic idea in active contour models or snakes is to evolve a curve, subject to constraints from a given image, in order to detect objects in that image. For instance, starting with a curve around the object to be detected, the curve moves toward its interior normal and has to stop on the boundary of the object. This model can detect the objects whose boundaries are not necessarily defined by the gradient. The segmentation boundary is represented with a level set function[10], which allows the segmentation to handle topological changes more easily[11]. This method doesn't require the images to be smoothed and works fine even on images with noise. This helps in the preservation of the object boundaries[24].

As Chan-Vese method preserves edges of objects, it is being used in most applications that has image segmentation as a step. Kovacs et al., (2012) [25] used chan-vese model to extract the building contours using the convex hulls of the point subsets, which belongs to edges in an defined directions, as initial contours. Karantzalos et al, (2009)[26] used a modified version of the Chan-Vese model to extract man-made objects from Aerial and Satellite imagery.

3.2 Methodology

The proposed method is mainly organized into two tasks:

- Object creation
- Object Attribution and Removal

Chapter 3

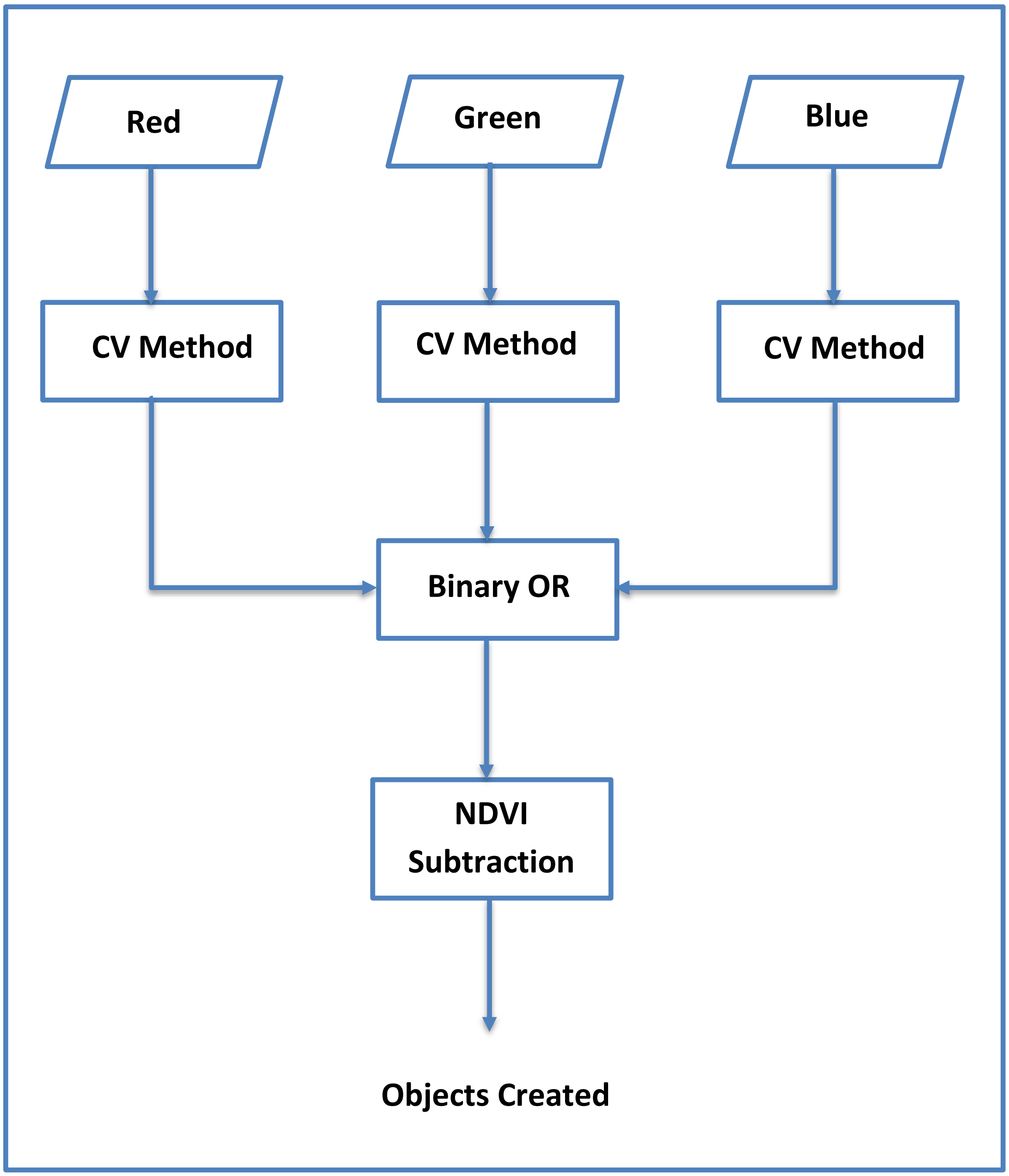

Figure 3.1. Objects Creation Workflow using CV Method

3.2.1 Object Creation

This step consists of creating objects by applying Chan-Vese segmentation on each of the visible bands of high resolution satellite imagery i.e, on red, green and blue bands to create objects. This is to ensure that all types of roof compositions will be detected in either of the three bands. The output of this segmentation step will be three binary images which are merged into a single binary image using the 'or' operator. This way we will have all the objects from the three bands even noise.

The chan-vese model classifies the trees and vegetation patches also as objects. We will use NDVI mask image to remove the vegetation objects. The NDVI mask can be created from the Near Infrared band and Red band of the satellite image using the formula[30]:

$$NDVI = (NIR - R) / (NIR + R) \qquad \text{- Equation 2}$$

This will give a binary image which has 1's at places of vegetation/trees and 0's at remaining places. After subtracting the NDVI mask from the CV output, the image will be free from vegetation objects.

3.2.2 Object Attribution and Removal

To remove noise and irrelevant objects, we used OBIA techniques. First, we applied morphological operations on the segmented image. This is to ensure that there are no linkages between the objects. we filled all the holes inside the detected objects and then performed a morphological opening operation. The opening operation removed any thin lines between two objects. These thin lines, if present, forces the two objects to be treated as a single object.

Next, we calculated features like Area, Perimeter, Roundness, width and height of the bounding box, Eccentricity of the ellipse that has the same second-moments as the region for all objects[29]. By imposing constraints on these features, we removed those objects which doesn't satisfy the requirements. These constraints are modelled such that they work for images of same resolution without any changes. For instance, we assumed that for a building, it is logical to have minimum dimensions of 6x6meters. For an image of spatial resolution 0.6meter, this would be 10x10 pixels. This indicates the minimum area of an object should be 100 pixels etc. So, we tried to remove all the objects that have less than 100 pixels area.

Chapter 4

Experimental Results

4.1 Data

We have used the Quickbird imagery of the Legaspi city, Albay District, Philippines. The data composes of one panchromatic band of 0.6m spatial resolution (1668x1668 pixels) and four multispectral bands(Red, Green, Blue, NIR) each of 2.4m spatial resolution(417x417 pixels).

4.2 Experiment and Results

First, we pan-sharpen all the four multispectral bands of 2.4m spatial resolution with high spectral resolution using the panchromatic band of 0.6m spatial resolution with high spatial resolution[27]. This will give us an image with both spectrally and spatially high resolutions (1668x1668 pixels). This is done using the pan-sharpening module of GRASS GIS 7.0 beta using IHS method [28]. The pan-sharpening is done on R,G,B at one time and on NIR,G,B at one time. Then we subset a portion of the image of (401 x 401) pixels with substantial buildings in it (fig 4.1).

Figure 4.1. Pan sharpened Legaspi Image

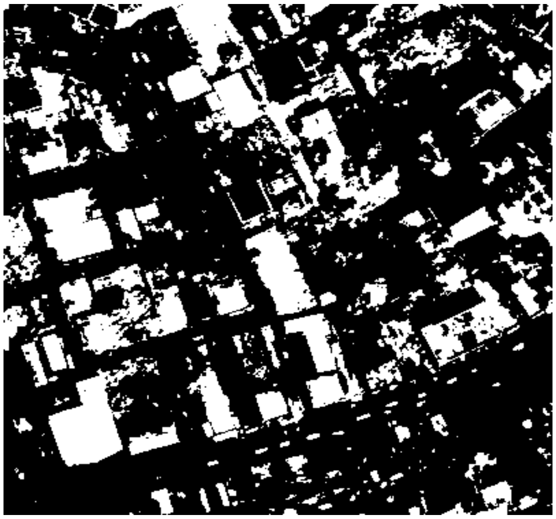

Figure 4.2. CV output of Legaspi Image

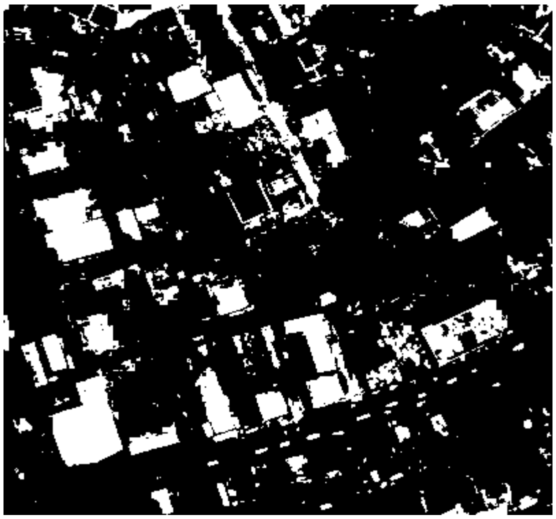

Figure 4.3. NDVI Mask subtracted from CV Output

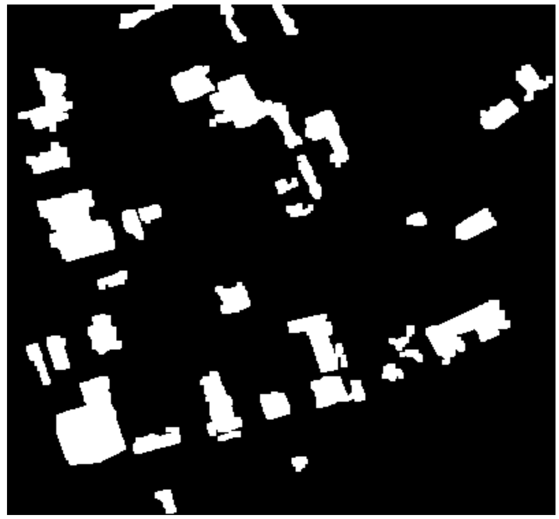

Figure 4.4. Final output of proposed method

We use matlab to carry out the following tasks. We apply the CV method on all the three bands (R,G,B) separately and then merge them using the binary OR operator(fig 4.2). We also create the NDVI mask of the same area and subtract it from the CV output(fig 4.3). Now we fill all the holes inside the objects and perform opening operation to remove links between objects. Then we calculate the required features like Area, Perimeter, Roundness etc. of each object.

As discussed earlier, we imposed constraints on the features and removed those objects which doesn't met the requirements. For the selected subset, we imposed that Area should be less than 25 pixels and if Area is greater than 25, we check the dimensions of the bounding box and eccentricity of the object. If any dimension of bounding box has less than 6 pixels or eccentricity greater than 0.98(indicating lines), we remove those objects. This constraint mostly eliminates the roads which are lines but get detected as buildings. The resulting image has large, moderate buildings as individual objects and clusters of small buildings as single objects(fig 4.4).

In the output, large and moderate buildings are almost detected. In fig 4.4, almost every building is detected as object. This might be because of the fact that all buildings in this scene are large or moderate range.

This method has its own shortcomings. In fig 4.4, two moderate buildings got grouped and been detected as one object. This might be attributed to very less gap between the buildings. In fig 4.4, the road segment is detected in multiple objects. The removal phase might not have detected them because of their large area and more width. Also, the road at one place merged with a building and being detected as one object.

The results show that approximately 73-77% of buildings got detected. Even if a small portion of building is detected, we considered it as correct one as we are concentrating on the quantitative measure. We have also excluded the results where one building got detected as two or more objects and two buildings got merged as one from the correctness measure.

4.3 Analysis

We analysed the results based on two criteria. One is analysis based on area overlap and the other is analysis based on building count.

4.3.1 Analysis based on Area Overlap

In this, we made an analysis based on how much of area under buildings in input image is actually marked as buildings in output. Based on this, we arrived at the following numbers for the mentioned image.

TP: True Positive **FP:** False Positive **FN:** False Negative

TP	FP	FN	Precision	Recall
14924	9264	2753	0.61	0.84

Table 4.1. Analysis based on Area Overlap in the Output Image

4.3.2 Analysis based on Building Count

In this, we made an analysis based on the number of the buildings that got detected. Even if a small portion of building is detected, we considered it as correct one as we are concentrating on the quantitative measure. We have also excluded the results where one building got detected as two or more objects and two buildings got merged as one from the correctness measure. The calculations for the mentioned image are as given below.

Input Count	**Output Count**	**Percent**
47	35	74.4

Table 4.2. Analysis based on building count in the Output Image

Chapter 5

Conclusions

In this study, we have proposed a semi-automatic method to extract large, moderate buildings and clusters of small buildings using Chan-Vese segmentation and Object Based Image Analysis techniques. The results show an approximate 73-77 % of building getting detected. The results seems to be promising in terms of quantitative accuracy which comes in handy for disaster management.

Future work can be done on applying the Chan-Vese model on false composites of the High resolution data. The building contours can be improved by using the method of building reconstruction which will help in map-updation and urban management. More semantic information can be incorporated into the model like the orientation of buildings etc., which is common in urban settlements[25].

Related Publications

1. S. K. Bypina and K. S. Rajan, "Semi-automatic extraction of large and moderate buildings from very high-resolution satellite imagery using active contour model," 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Milan, Italy, 2015, pp. 1885-1888.

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