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Building Detection in Satellite Image using Firefly Tuned Grab Cut Algorithm

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Abstract: A robust building detection methodology is proposed in this paper unlike classical classification methods, where self supervision data can be automatically extracted from the image by using shadow and its direction as an invariant for building object. In this methodology; first the vegetation regions are detected from a given satellite image and local directional fuzzy landscapes representing the existence of building are generated from the shadow regions using the direction of illumination obtained from image metadata. For each landscape, foreground (building) and background pixels are automatically determined and a bi partitioning is obtained using a graph-based algorithm, Grabcut, which is further modified by an iterative bio inspired optimization: Firfly Algorithm. This work towards the optimization k-means clustering used in grab cut method.

Keywords: Geographical Information System (GIS), Normalised Infra red (NIR) band, firefly algorithm.

I. INTRODUCTION

With the rise in satellite communication it is required now to process the high resolution satellite image in various applications. For security and surveillance purpose detection and segmentation of objects in high resolution satellite image is utmost required. The satellite image is hyperspectral image which have more than three bands. The wavelength intervals of color bands of a satellite image are different than that of an RGB image.

Also, the spectral resolution of an RGB image is 8-bit (255 levels) by default; whereas the spectral resolution of a satellite image, in most cases, is different than 8-bit. Considering these discrepancies, the problem of clearly and sharply displaying a satellite image arises. In order to overcome this, widely known Geographical Information System (GIS) toolboxes such as ERDAS Imagine, PCI Geomatica use some image enhancement methods. These can vary from very simple image adjustment and contrast stretching operations to complicated enhancements using closed nonlinear transformations.

The satellite image can be visualized by using red, green, blue channels as its standard order (called true-color), as well as mapping NIR, red, green channels to red, green, blue. This is called false-color. This visualization is much useful for identifying vegetative regions. Figure 1.1 shows an example satellite image in true-color and false-color respectively.

In addition to the image data, the high resolution satellite image products are obtained with a text metadata file. This file covers all relevant information about the satellite image; including geographic coordinates of the image corners, date and time the image had been acquisited, geometric resolution of the image file, the name and type of the optical satellite sensor, the altitude of the sensor and the sun azimuth / zenith angles at the image acquisition time.

(a) (b)

Figure 1.1: A satellite image shown in two different visualizations. (a) True color visualization.(b) False color visualization [23].

The direction of illumination, which is simply the opposite of the sun azimuth angle, provides valuable information for detecting potential building regions when combined with the detected shadows. These will be explained in further chapters.

Figure 1.2 shows an illustration of sun azimuth and zenith angles, and the direction of illumination.

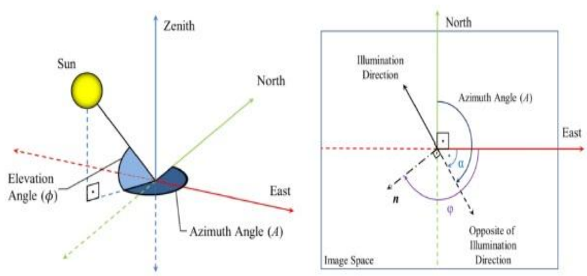

Figure 1.2: Illustration of solar angles in 3-D space and image space. (a) Sun azimuth (A) and zenith (∅) angles. (b) Direction of illumination in image space [6]

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II. METHODOLOGY

Proposed work is discussed into two steps. In the first part shadow detection followed by extraction of vegetation mask form the high resolution satellite image is discussed and in teh second part proposed enhancement is discussed.

Shadow and Vegetation area detection

As discussed hyper spectral image have four bands unlike three bands in conventional RGB image. The fourth band is Normalised Infra red (NIR) band which contains the illumination information of image. To detect vegetation area and shadow, this information is very helpful. The most widely used index is Normalized Difference Vegetation Index (NDVI). The formula for calculating NDVI is simply [6]:

$$\rho_{NDV1} = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED} \qquad (2.1)$$

Where ρNIR and ρRED represent the reflectance values for near-infrared and red bands respectively.

For every pixel, the ρNIR is calculated and an NDVI map is generated for whole image. The decision whether a pixel belongs to a vegetated area or not is made by simply applying Otsu's automatic thresholding method. Figure 2.1 shows an example image of detected vegetation regions in a residential area:

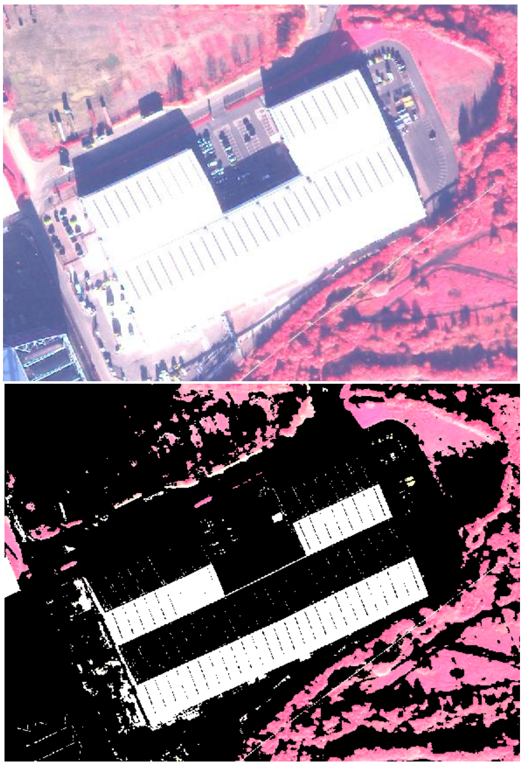

Figure 2.1: (a) Input Image (b) vegetation area detected

Detection of Shadows

The approach generates a false color image in which NIR, red and green bands are employed. The algorithm is simple; first, the false color image is normalized and converted to Hue-Saturation-Intensity (ρ_{HSI}) color space. Then, a ratio map (ρ_{RM}), in which the normalized saturation (ρ_S) and the normalized intensity (ρ_I) values are compared with a ratio, is generated [6]:

$$\rho_{RM} = \frac{\rho S - \rho I}{\rho S + \rho I} \qquad (2.2)$$

To detect the shadow areas, as utilized in the case of vegetation extraction, Otsu's method is applied to the histogram of the ratio map, ρ_{RM}. Due to the fact that the thresholding scheme detects both shadow and vegetation regions at the same time, the regions that belong to the vegetation are subtracted to obtain a binary shadow mask. This approach provided successful shadow detection results for various satellite images and the major advantage is that it is independent from manual thresholds. Figure 2.2 shows examples of detected shadow regions.

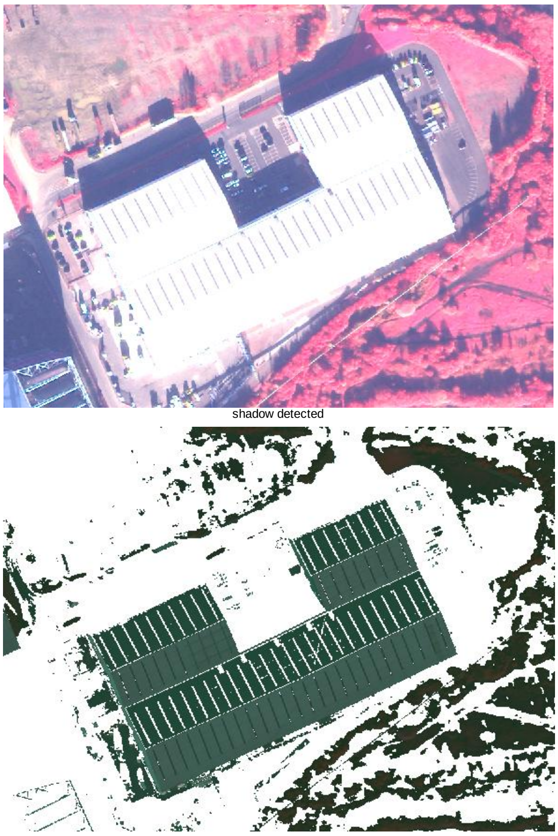

Figure 2.2: Shadow detection example. (a), Sample images. (b) Shadow detection results of (a), (c).

Proposed Enhancement

In the grab cut method to extract the foreground object which is building image in our case, k means algorithm followed by Gaussian mixture model is used which provide label to pixels. If pixel belongs to background '0' label is assigned and if it belongs to foreground then label '1' is assigned to that pixel. K-means classification method is based n random search of centroid which may lead to jump over local minima some times. Due to this pixel can be classified to false class. To avoid this we have used firefly optimisation in place of k means which is not suffering from this problem. The working of firefly algorithm is based on movement of firefly. It is considered that it is unisex and attracts to each other by their light. Higher the intensity of light, more fireflies will attract towards that. In our application firefly's light is correlated to objective function value which is the minimum distance between centroid co ordinates and pixel co ordinates.

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Movement of other fireflies, which are centroid co ordinates of foreground and background pixels, is towards the minimum distance sum of objective value. Mathematically it can be represented as:

$$obj\ value = \sum_{i=1}^{n} \sqrt{(x_2 - x_i)^2 + (y_2 - y_i)^2} \qquad (2.3)$$

Where x_2 and y_2 are the co ordinates of centroid and x_i, y_i are the image pixels co ordinates.

Initially centroid co ordinates are initialised randomly like k means and objective function is calculated for that, value is stored in a matrix. Now position of fireflies (centroid co ordinates in our case) is updated as per stated in mathematical expression [22]:

$$x_i^{t+1} = x_i^t + \beta \exp\left(-\gamma r_{ij}^2\right)\left(x_j^t - x_i^t\right) + \alpha_t \varepsilon_t \qquad (2.4)$$

Where the second term is due to the attraction. The third term is randomization with α_t being the randomization parameter, and ε_t is a vector of random numbers drawn from a Gaussian distribution or uniform distribution at time t [28]. The attractiveness of fireflies depends upon the distance so it varied exponentially with distance from other justified by the following mathematical expression [22]:

$$\beta = \beta_o e^{-\gamma r_{ij}^2} \qquad (2.5)$$

Where β_o is the attractiveness parameter and 'r' is the distance between two fireflies. α_t is the factor for random control of fireflies. It can be tuned during iterations to achieve best result. Usually it is mathematically defined as [22]:

$$\alpha_t = \alpha_o \delta \qquad (2.6)$$

Where α_o is initial randomness factor and δ is the cooling factor. For most applications it is in between 0.95-0.97.

Updating the firefly position using equation 2.4 new co ordinates for the centroid are obtained for which objective function value using equation 2.3 is calculated and saved again. The minimum value amongst all iterations is the minimum distance amongst all pixel labels and co ordinate for which this minimum values is obtained is the final centroids.

III. RESULTS

This chapter is dedicated to show the outcome of proposed work and methodology described above, we have used some data base of satellite images and algorithm has been tested over that.

MATLAB is used a tool to develop the script for the work. It provides a wide range of in built toolboxes including image processing which makes our work easier. Since the input images used were of very high resolution, these requires a high memory in MATLAB, so we downscaled them upto 20% and now algorithm, execution takes less time. A sample of input image is shown in figure 3.1.

Satellite image is different from TGB image as it consists four frequency bands alike three in RGB and as discussed earlier to represent the image we need to use some dedicated tools, default MATLAB don't have those. So we constructed a false image in which three bands are illumination information, red band and green color band. Above image is result of that. This image is converted into gray scale image to make memory requirement less without significant information loss. Now first of all vegetation mask is obtained as per formula given in equation 3.1. figure 3.2 shows the vegetation mask generated for input image of figure 3.1.

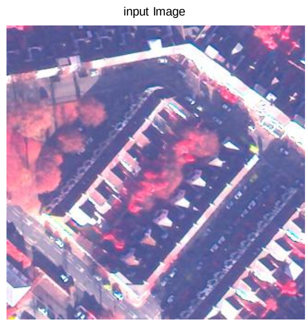

Figure 3.1: input satellite image of high resolution [23]

Figure 3.2; vegetation mask generated by equation 2.1

The false image initially created is converted to HSV color map to get the shadow mask of buildings. Initially all shadow are generated by normalized difference of saturation and value of HSV map. Outcome is shown in figure 3.3.

Now figure 3.3 and 3.2 matrices are subtracted to get only shadow mask of buildings. Subtraction will remove the vegetation shadows and all other objects shadow form the image, leaving only building's shadow behind as shown in figure 3.4. These shadows are shown on the original image in figure 3.5 below. Further refinement is required to automate the process of grab cut to detect the buildings and to remove small shadows which can be of tress or vehicles.

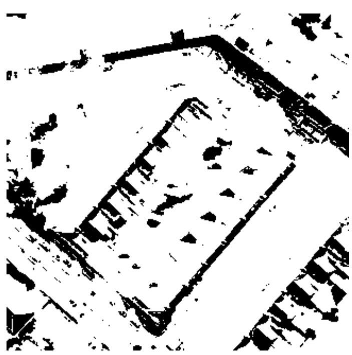

Figure 3.3: shadow of all objects in the image

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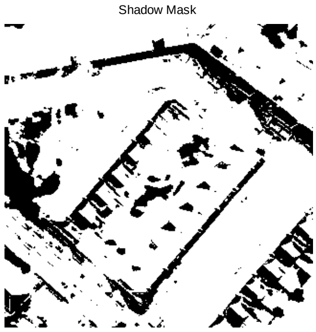

Figure 3.4: shadow mask of buildings.

For this we have taken a threshold of 3 m height. Shadows less than this height are removed from the picture. This is done by fuzzy landscape method. Landscape generated by this is also used to automate the semi automatic grab cut method. The refined shadow map is shown in figure 3.5.

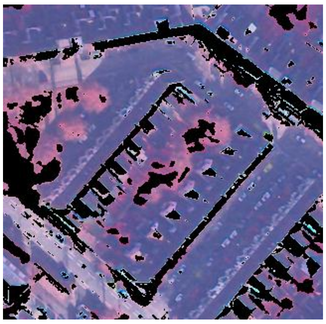

Figure 3.5: Refined shadows after fuzzy landscape

We have assumed in this case that shadows are started along the building boundaries, so considering the illumination angle of sun from meta data file which comes along with the satellite image, pixels next to shadow area in the direction of illumination are treated as building boundaries. Further by optimizing the grab cut by forefly optimization building detected is shown in figure 3.6.

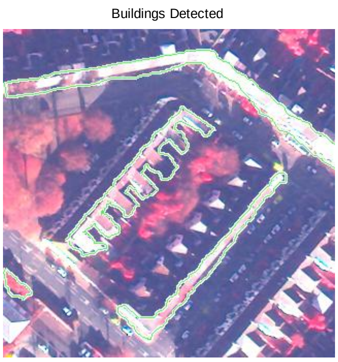

Figure 3.6: Building Detected

IV. CONCLUSION

This work proposed a new automated building detection methodology in high resolution satellite images. The vegetation, water and shadow regions are detected from a given satellite image, and local fuzzy landscapes are generated from the shadow regions using the direction of illumination obtained from image metadata. Afterwards, for each fuzzy landscape, foreground and background pixels are automatically determined and a bi partitioning is obtained using a graph-based algorithm called Grabcut. The grabcut method is not automatic, it need human intervention and plotting of bounding box in the image for the area which need to segment. We have made this process fully automated by fuzzy landscape which made blobs of shadow areas. The grab cut algorithm is based on k means classification so we have replaced k means by a bio inspired firefly algorithm. In our work no manual supervision of user interaction is required. Instead; the supervision data is automatically generated inside the algorithm, using shadow cues.

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