Topic Name / Title

Applied Digital Image Processing

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1 Abstract

2 Introduction

In the context of our present ecological challenges, addressing and raising awareness about global warming stands as a paramount imperative. Given the limitations in resources and the potential reluctance of governing bodies to prioritize this issue adequately, it becomes essential to pioneer a systematic approach for monitoring, reflecting upon, and mitigating these environmental changes.

Our primary objective is to institute a meticulous process for the collection and analysis of satellite imagery. Subsequently, we intend to apply various advanced methodologies and mathematical algorithms to these images. This multifaceted approach serves a dual purpose: it helps in our ability to fairly analyze and document alterations in land topography brought about by climate change upto an approximate degree, while also diminishing our reliance on local authorities and potential vested interests that may obstruct progress in this crucial area.

By implementing this approach, we aspire to foster greater transparency, accountability, and data-driven decision-making in the quest to combat global warming. Moreover, this initiative carries the potential to engage and enlighten the public about the pressing need for environmental conservation, ultimately leading to a more sustainable and resilient future for our planet as we try to compare and contrast different classical digital image processing techniques with the current state of the art method.

Our project aims to utilize the capabilities and functionalities of classical digital image processing for the purpose mentioned above that can be done using satellite imagery and images from Google Earth. Deforestation is a major contributor towards the global boiling, as environmentalists term it now (instead of global warming). The monitoring system can contribute towards helping the relevant stakeholders to make better informed decisions through sustainable development. [1]

3 Literature Review

This section entails a review of the previous work done in the scope of detecting deforestation using different types of satellite imagery. Most of the techniques use remote sensing, i.e., making use of the satellite imagery to detect image change and deforestation. While the methods in section 3.1 and 3.2 work on single band images, section 3.3 and onwards work on multi-band images which is the current state of the art procedure.
Our project aims to bring classical techniques and compare their results with the more accurate methods to see if the classical methods can be used to have a fair estimate of the deforestation since the acquisition of multi-band satellite imagery and the pre-processing required is cumbersome and cannot raise public awareness.

3.1 Image Clustering

Content Based Image Clustering (CBIR) is a method used to group or classify objects into different classes which have similar properties. These classifying of images help us study different characteristics of

This classifying of images into groups help assist study different characteristics of the image like better flow, pattern changes and similarity of events or phenomenon. Further clustering of images gives clusters or regions with detailed and concise information and the content of the images which ease the task of asserting this regions of clusters.

The Fuzzy C-Means (FCM) clustering method [2] is based on minimizing the following objective function:

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^m \cdot \|\mathbf{x}_i - \mathbf{v}_j\|^2 \tag{1}$$

Here's a breakdown of the terms:

- J_m is the objective function to be minimized.
- n is the number of data points.
- c is the number of clusters.
- u_{ij} is the degree of membership of data point $\mathbf{x}_i$ to cluster j.
- m is a weighting exponent, usually set to 2 for FCM.
- $\mathbf{v}_j$ is the centroid of cluster j.
- $\|\mathbf{x}_i - \mathbf{v}_j\|^2$ is the Euclidean distance between data point $\mathbf{x}_i$ and the centroid $\mathbf{v}_j$.

The objective is to find the membership values u_{ij} and cluster centroids $\mathbf{v}_j$ that minimize the objective function. The degree of membership u_{ij} indicates the fuzzy assignment of data point $\mathbf{x}_i$ to cluster j, with higher values indicating stronger membership.

FCM (Fuzzy C-mean) is one of the most common form of image clustering and it is the based on the principle of fuzzy classification. In fuzzy C-mean clustering pixels with identical properties will be grouped into to same categories or clusters. [Cite 2 Doc 22]

The input images of the fuzzy C-mean clustering, where Gray scale images and the cluster centers were computed automatically by the function itself. Once the cluster center was found and fixed, the next stage was setting the rules for fuzziification. That is if-then rules are given below assuming that the three cluster values are cluster 1, 2 and 3.

- If pixel (i,j) is less than Cluster-1, center make it black(0)
- If pixel (i,j) is greater than cluster-3 center make it White (1).
- Else make pixel (i,j) in between black and white (0.5).

The FCM algorithm continuously upgrades and moves this cluster centers iteratively to the ideal or right position. So by continuous moving of initial cluster centers, it precisely clusters the image into different regions and groups the accuracy of the membership grades of each groups [Cite3 in 23 in Doc].

3.2 Otsu Method on color spaces

Image Segmentation is seperating or dividing of images into different clusters or regions based on common properties and/or differences between other regons properties. One property out of the many could be applied to separating images into regions is pixel intensity.

The method involves finding an optimal threshold that minimizes the intra-class variace of pixel intensities:

$$\sigma_w^2(t) = w_1(t) \cdot \sigma_1^2(t) + w_2(t) \cdot \sigma_2^2(t) \tag{2}$$

Where:

1. t is the threshold value.
2. $\sigma_w^2(t)$ is the weighted sum of the variances of the two classes spearated by the threshold
3. $w_1(t)$ and $w_2(t)$ are the probabilities of the occurences of the two classes separated by the threshold.

4. $\sigma_1^2(t)$ and $\sigma_2^2(t)$ are the variances of the two classes separated by the threshold.

The goal here, is to find the threshold value t which effectively spearates the image into two classes, that minimizes the intra-class variance and maximizes the inter-class variance. [3]

So we normally can segment images into different regions through thresholding or separating the pixel levels into different scales. These different thresholding scales create different regions corresponding to the pixel intensity values.

A simple example can be thresholding a gray scale image pixels into two regions, by transforming the gray scale image into binary image, which will consist of only two regions, namely either the black or white.

If $G(x, y)$ is a threshold version of $f(x, y)$ at some global threshold T,:

$$G(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geq T \\ 0 & \text{otherwise} \end{cases}$$

This method has been used with color spaces like HSV (Hue, Saturation, Intensity), and L*a*b* to identify areas of deforestation that we will further see in the methodology section.

3.3 Change Vector Analysis

The change vector analysis [4] involves two variables, the magnitude of variation and the angle of the change vector. The change vector is obtained by subtracting the images represented in vector form. The first step of the CVA method is to find (Normalized Difference Vegetation Index) NDVI and (Bare Soil Index) BI values of both the images.

$$NDVI = (NIR - RED)/(NIR + RED) \tag{3}$$

$$BI = ((SWIR + RED) - (NIR + BLUE))/((SWIR + RED) + (NIR + BLUE)) \tag{4}$$

where NIR, RED, $SWIR$ and $BLUE$ are the spectral reflectance measurements acquired in the near-infrared, red, short wave infrared and blue regions. Change vector of each pixel includes two components NDVI and BI, which are the 2 axes in Cartesian coordinate system. The start point and finish point of the change vector are the locations of pixel in NDVI-BI space. The magnitude of vector represents the change intensity and the direction of vector represents the change dimension Further calculations not only allow us to furhter divide the values into two different groups which do not only allow to see the land and forestation/plantation affected.

3.4 NDVI Method

This method entails the use of multi-band satellite imagery to detect and produce results for areas of vegetation [5] where the Landsat 8 has eight bands: blue, green, red, near-infrared 1, near-infrared 2, thermal, mid-infrared, panchromatic. All of the bands have 30 meters resolution, except thermal with 60 and panchromatic with 15 meters of resolution (GIS Geography, 2017, USGS, 2017)
Picked bands of the imagery are band 2, band 3 and band 4, representing, green, red and near infrared bands. These bands are selected since they are used in the calculation of the NDVI. NDVI calculation is shown in equation below:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{5}$$

where NIR and RED are the near infrared and red bands respectively.
Cropped images of these three bands are combined to form a false color composite image. Three other metrics are used, namely accuracy, precision, and recall.

Recall metric represents the rate of the correctly identified vegetated regions and calculated as TP / (TP + FN). On the other hand, precision indicates what percentage of the regions found as vegetation are actually true with respect to ground truth and calculated as TP / (TP + FP). Using precision and recall, we can calculate an fScore value for prediction of vegetated regions, which is a score varies in [0, 1] range. The higher the score value, the better the result is. The formula for fScore is shown in equation 3.

$$fScore = \frac{2 * Precision * Recall}{Precision + Recall} \tag{6}$$

where Precision is the precision value for the case, Recall is the recall value for the case, and $fScore$ is the resultant $fScore$ that shows how good the result is.

Moreover, the vegetation ratio is also used to examine the loss in vegetation areas. Here, the total number of pixels with value 1 are divided by the total number of pixels.

$$VegetationRatio = \frac{TotalNumberofPixelswithValue1}{TotalNumberofPixels} \tag{7}$$

3.5 Wavelength Method

The data was processed and the analysis was by determining the wavelengths of certain frames from Landsat-7 and four frames from Landsat-8. The bands were combined for each frame and the null values were eliminated using the Copy Raster toolset. Finally, mosaicing was done on the frames for each year separately using the Mosaic to New Raster tool.

The spatial-temporal variability of normalized difference vegetation index NDVI was assessed to study deforestation using harmonic analysis. We first spatially normalized observations to reduce seasonality. Subsequently, we detected deforestation by assessing whether a newly acquired observation (satellite image) in the monitoring period is in an extreme change when compared against spatially normalized values in present time data defined over a reference period. The calculation of the NDVI for multi-date satellite images of Landsat (7, 8) was used to perform change detection of the deforestation in Huambo Miombo.

The NDVI, as one of the most successfully used vegetation spectral indices, allows comparison between inter-annual and seasonal changes in vegetation. The NDVI measures the amount of green vegetation in an area and is used to distinguish forested from deforested areas.

Landsat 8			
Band	**Wavelength**	**Application**	**Resolution (m)**
Band 2—Blue	0.452–0.512	Bathymetric mapping, distinguishes soil from vegetation and deciduous from coniferous vegetation	15
Band3—Green	0.533–0.590	Emphasizes peak vegetation, which is useful for assessing plant vigor	15
Band 4—Red	0.636–0.673	Discriminates between vegetation slopes	15
Band 5—Near Infrared (NIR)	0.851–0.879	Emphasizes biomass content and shorelines	15
Landsat 7			
Band 1—Blue	0.45–0.52	Bathymetric mapping, distinguishes soil from vegetation and deciduous from coniferous vegetation	30
Band2—Green	0.52–0.60	Emphasizes peak vegetation, which is useful for assessing plant vigor	30
Band 3—Red	0.63–0.69	Discriminates between vegetation slopes	30
Band 4—Near Infrared (NIR)	0.77–0.90	Emphasizes biomass content and shorelines	30

Figure 1: Landsat Satellite Sensor characteristics

4 Methodology

5 Results

6 Conclusion

References

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