UNCOVERING TRANSFORMATION IN FOREST TERRITORIES THROUGH IMAGE ANALYSIS

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Abstract - The work is change transformation in forest territory through image analysis. The primary natural resource in charge of maintaining climate stability and acting as a carbon sink is the forest. It also makes a major contribution to a nation's social, economic, and cultural advancement. Deforestation and changes in Land Use and Land Cover (LULC) have been occurring for the past few decades because of an increase in mining activities and human encroachment. Thanks to recent developments in remote sensing technologies, we can now estimate the extent of these changes in forest regions and LULC modifications. Worldwide, deforestation and forest degradation caused by human activity pose a danger to forest reserves. Maps of deforestation, forest degradation, disturbances, and the forces behind them are created using satellite imagery and data collected on the ground. The process is achieved by collecting Multi-temporal images from satellite using SIFT ALGORITHM. This system can support responsible forest management practices, ensuring the long-term viability of these natural resources.
Keywords: Deforestation, land use/ land cover change, unsupervised categorization.

INTRODUCTION

Research on the environment is increasingly using remote sensing. Satellite photos were largely utilized as a background for maps or for simple interpretations in the 1970s and 1980s [1]. For the last three decades, topographical, meteorological, and geological applications have effectively employed satellite imagery. Deforestation Is a primary contributor to global warming.[2–3].

The rise in green house gas emissions from surrounding areas is what causes global warming [3]. Deforestation increases the effects of global warming by removing areas with dense forests, which lowers the number of plants thatabsorbCO2.[4]

Unintentionally, deforestation upsets the delicate balance between carbon dioxide absorbed and produced. The process of detecting differences between two remotely sensed photos taken over the similar area at various times is known as "change detection from pictures"[5–6]. When it comes to altering identification for land use, SAR sensors are more suited than other remote sensing methods because they are less vulnerable to the environment, especially to clouds and rain. Because of this, it has been successfully used in several applications over the past few decades, such as damage assessment, urban studies, agricultural surveys, environmental monitoring, and forest monitoring [7]. The functioning of the Earth system is significantly impacted by these changes. Additionally, when the population grows, more demands are placed on the earth's finite resources, which further alters the land surface over [8].

Globalization, urbanization, agricultural intensification, and forest degradation are some of the main factors influencing regional and worldwide shifts in land cover and usage. Numerous sources have identified globalization, urbanization, agricultural intensification, and forest degradation as the main drivers of changes in land use and cover at the regional and global levels[9–10].

Global climate, ecosystem activity, and biophysical characteristics are all correlated with significant variations inland cover. The information needed to comprehend how land

use has changed in a coastal area[11].Both land cover and land utilization are always changing and dynamic. Accurate and up-to-date maps of land use and cover are essential for proper planning, global change monitoring, environment al monitoring, and forest degradation prediction [12–13].

2 SYSTEM MODEL

Figure 1 displays the flow chart for the suggested system. It displays the content of the two photos that are gathered, given filters, and then processed to create a different image by analyzing the images to produce a map that detects changes. Figure 2 displays the algorithm's work flow. The recommended approach to change detection is not predicated on any of the current techniques.

For a thorough knowledge of the dynamics of the landscape during a given era, LULC identification is essential. It's possible that LULC is a well-known and sophisticated process that's largely caused by human activity and natural events, which have changed the physical environment's characteristics. Results and Comparitive an Alysislulc associated with human activity which has been regarded as the primary source bringing exceptional speeds, magnitudes, and geographical extents to this process, even though several factors cause global environmental changes. One of the most important aspects of LULC is Tropical forest regions being transformed into various types of land, such vast agricultural fields, and the primary function of LULC in tropical countries is the spread of agriculture. It is acknowledged that Land modification has created a risk to the disappearance of forest covers and ecological services.

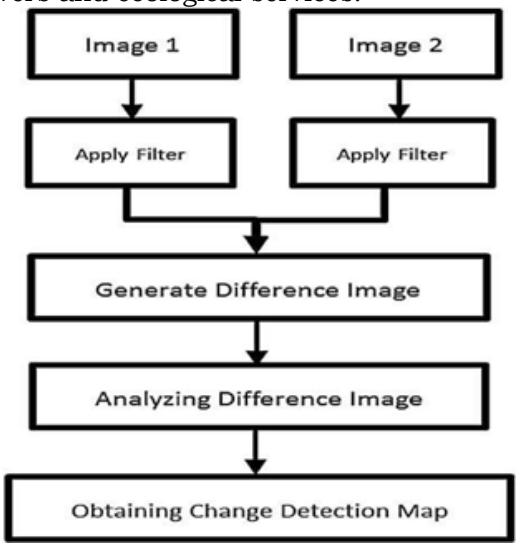

Figure1 Content diagram of project

By blending red, green, and blue light in various ways, the RGB color model is an additive color model that simulates a wide range of colors. The dimensions of every color channel are the same, as are the number of rows and columns.

A matrix with dimensions of 1000 x 1000 x 3 is the mathematical representation of an RGB image[1,2]. Finding changes in an area of interest that have arisen due to natural or artificial forces is the process of change detection.

A post-processing task called "change detection" is used on photos of the area of interest that were taken at various periods. Without requiring the extraction of features or objects, there are numerous methods for spotting changes in RGB and high-resolution pictures based on the data pixel in the image. The RGB-NDVI, or Normalized Difference Vegetation Index from RGB Image, is a precise pixel-based representation used to track the removal of tropical forests and the regeneration of vegetation. Using multispectral signals, object reflectance is extracted. For the detection of forest changes, the OB- Reflectance method yields results that are somewhat more accurate than the RGB-NDVI pixel-based method.

3 RESULTS AND COMPARITIVE ANALYSIS

This section's Figure2(a) displays a Google Earth satellite image that was captured in 2018 of a randomly selected topographical region utilizing satellite technology. Contrasted with the same terrain after a two-year period, and Figure 2(b) displays a Google Earth satellite image captured in 2020 of a randomly selected geographical location, juxtaposed with the terrain from the previous two years.

(a) (b)

Figure 2(a): Google earth satellite earth of terrain area during the year 2018

Figure 2(b): Google earth satellite earth data of terrain area during the year 2020

The most popular method for converting different informational arrangements into a one-way framework is picture enrolment. Information can include various pictures or data from different sensors at different times, depths, or perspectives. Applications for this type of information include therapeutic imaging, PC vision, military programmed target recognition, and the organization and analysis of satellite imagery and data. To beable to organize or analyse the data gathered from these disparate approximations, enrolment is essential.

The depiction of the two images that are being compared above in the change detection approach using the SIFT and SAR methods is shown in Figure3.

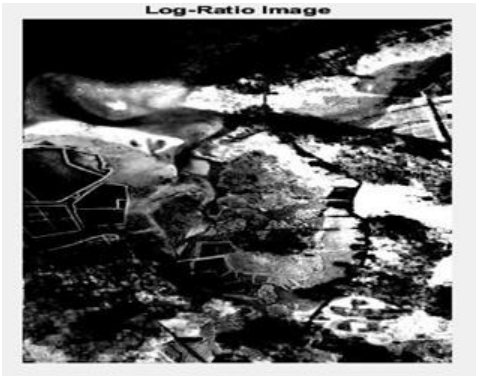

Figure 3: Log Ratio Image

Figure 3 likely originates from two separate SAR images of the identical area. These two images are captured at Disparate times. The variations in brightness a cross the image represent the relative changes that occurred between the two captured instances.

SIFT TECHNOLOGY

The further process after generating the log-ratio is performing (Scale Invariant Feature Transform) SIFT technology. During this step, the picture characteristics and key-points are identified. For Space-Scale invariant image processing, (Difference of Guassion) Do Gpyramids provide an efficient format. Keyspots are determined as local minima/maxima of

DoG pictures across scales after DoG images have been acquired. It is identified as a possible key point if the pixel valueis the greatest or least among all compared pixels. Extrema is any point at which value of image is largest or smallest. The visual qualities of the image content are described by picture descriptors. They explain fundamental aspects of pictures, such shape, color, texture, and motion. Objects in the world have the intrinsic quality of only being meaningful entities within specific scale ranges. A circular picture area with an orientation is called a SIFT key point. A geometric frame with four parameters describes it. As the SIFT algorithm, the Speeded Up Robust Features (SURF)algorithm search about the orientation of the point by in the DoG images, every pixel is compared to eight neighbors at the similar scale and nine neighboring pixels that are equal in each neighboring scale making directions and sizes. Key spots are determined as local minima/maxima of DoG pictures a cross scales after DoG images have been acquired. DoG images pixels are compared to their eight. Extrema is any point at which value of image is largest or smallest. If neighbor's at the same scale and nine equivalent nearby pixels in each of the neighboring scales. It is chosen as a potential key point if the pixel value is the greatest or minimum among all compared pixels. They explain fundamental aspects of pictures, such color, form, texture, and motion. They explain fundamental aspects of pictures, such color, form, texture, and motion.

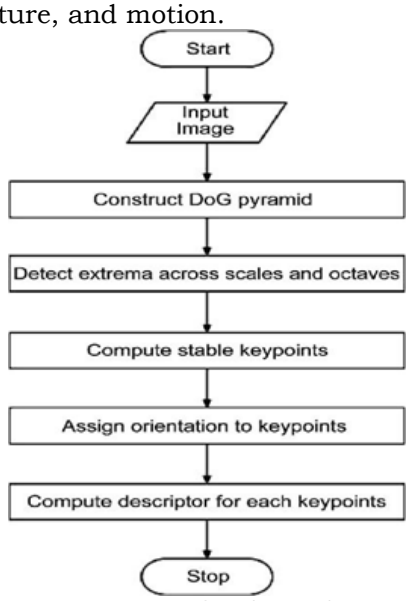

Figure 4 Sift Algorithm

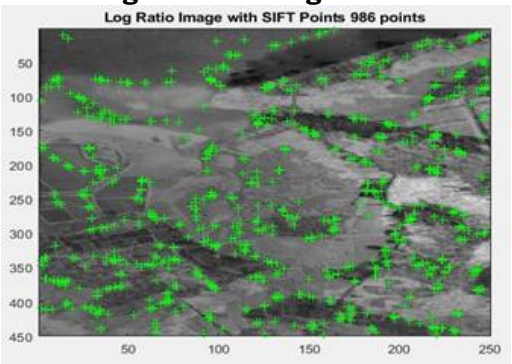

Figure 5: Log ratio image with SIFT points 986 points

log Ratio Image: This indicates that the picture is formed by equating two separate SAR photos of identical area.

986 SIFT Points: SIFT stands for Scale-Invariant Feature Transform. These points likely represent distinctive features identified with in the image that are invariant to scaling and rotation. They might be used for image registration or other image processing tasks.

The recommended approach to change detection is not predicated on any of the current techniques. The change detection method compares two sets of colour channel values for all pixel in the input figure of the research region with the matching one.

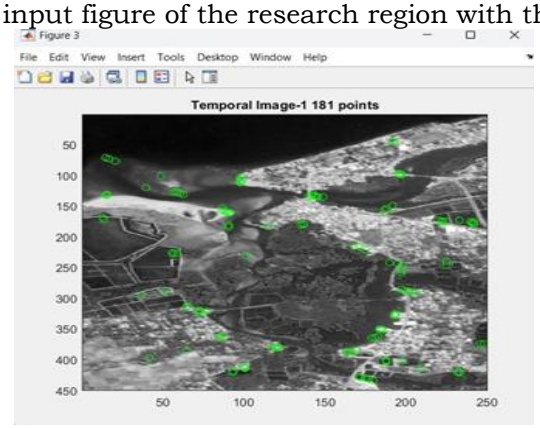

Figure 6: Temporal Image-1181points

Figure shows the 181 points of thetemporalimage1in point feature matching.

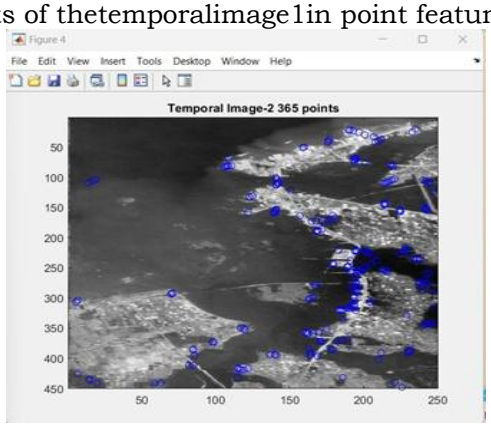

Figure 7: Temporal Image-2365 points

Figure shows the 365 points of the temporal image 2 in point feature matching.

From figure 6 & 7 To Identify the SIFT points from both images we will take surroundings of the SIFT points as a reference. These references are commonly known as vectors. Some randomly SIFT points are taken which are of high stability. Laterthefigure7 is compared with the figure 6 (the SIFT which are having the high stability of location are compared in both images.) The places which are unchanged in both images will keep remained with previous SIFT points.

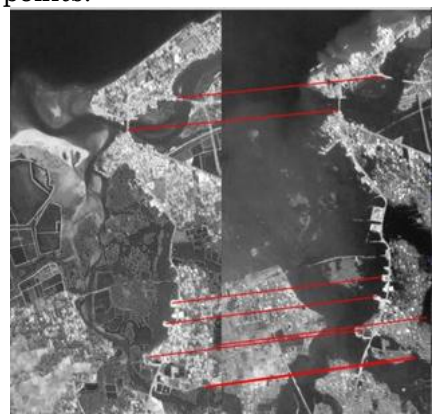

Figure 8: Region Location Mapping

Figure 8 shows a comparison of the two photos and Indicates the are as where the images have unchanged

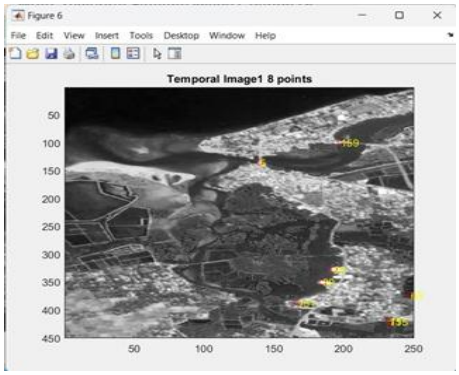

Figure 9: Temporal Image-18points

Figure shows the 8 points of the temporal image1in Region Location Info. The comparison lines which are shown in theabovefigure8 are showing in the figure 9 with their information.

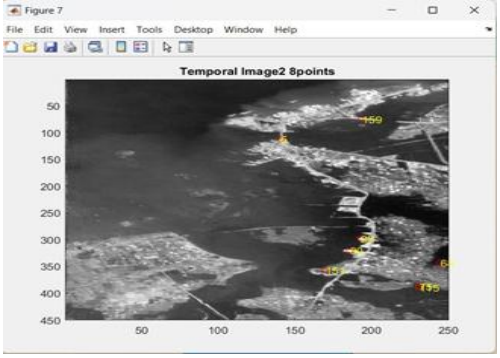

Figure10: Temporal Image-28points

Figure shows the 8 points of the temporal image 2 in Region Location Info. The comparison lines which are shown in the above figure8are showing in the figure10 with their information.

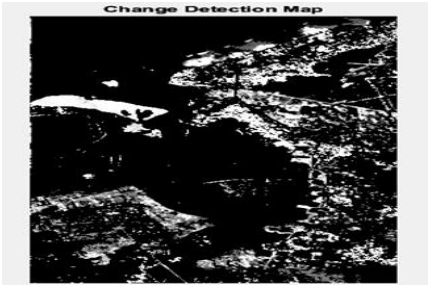

Figure11: Change Detection map.

The final change detection map of the two inserted landscape photographs from different years is shown in the above figure, and it is being compared using both SIFT technology and Log image

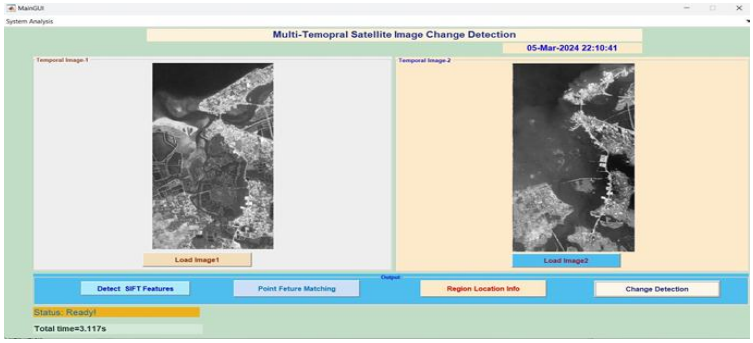

Figure12. Elapsed time of proposed method

4 CONCLUSION

One of the key picture processing methods in distant detecting is image registration, which has been studied and developed for a good amount of time. However, not so long ago, it is nevertheless intriguing to observe as a precise, potent, and planned image enlistment method, and the majority of picture enlistment tactics currently in use are meant for implementation. While high goal remote sensing imagery has currently made it easier for people to focus on the planet, it also presents certain challenges for traditional exploration techniques. Regarding photo enrollment, there are a few problems with the way that high goal images are currently enrolled in photos right now, namely:

(a) Clearly identifying control foci is more difficult than it seems, much like with moderate goal images:
(b) Physically selecting the vast array of control focuses required for precise enrolment are dull and laborious.
(c) a large amount of information will negatively affect the processing speed in the picture enlistment; and
(d) even with adequate control focuses, nearby mathematical mutilation would not be effectively eliminated using conventional picture enlistment techniques.

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