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Analysis Of Harmonic Analysis For Signal And Image Processing Applications

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Abstract

Harmonic analysis is a fundamental tool in signal and image processing that is essential to many applications, including pattern identification, audio and speech recognition, image compression, and many more. In-depth discussion of harmonic analysis methods and their relevance to signal and image processing are provided in this study. This work proposes a novel method for classifying land features and detecting hotspots based on harmonic analysis of NOAA/AVHRR annual composite pictures. Due to their extensive coverage, high frequency, and free availability, the NOAA/AVHRR photos were chosen. Three steps make up the proposed algorithm's primary section. In order to rectify geometric distortions and perform radiometric calibration of the data, the NOAA/AVHRR photos first go through preprocessing. As a result, measurements are reliable and constant across the whole time period. The preprocessed images are used to identify cloud and water pixels, and harmonic analysis is used to examine the 10-year time series of AVHRR images. The NDVI (Normalised Difference Vegetation Index) and various AVHRR band values are temporally changed in the phase and amplitude images created by the harmonic analysis. While the amplitude information represents the size of these shifts, the phase information sheds light on their time and frequency. Images of various bands' amplitudes are processed using image-processing algorithms. The objective of this stage is to identify hotspots, or places that have undergone major changes over time, and to categorise the region of interest using these traits. The proposed method produced categorization results with a high accuracy rate of over 91%.

Keywords: Image processing, NOAA/AVHRR, time series, normalization.

I. Introduction

The domains of signal processing and image processing have made great use of the potent mathematical technique known as harmonic analysis. It entails breaking down intricate signals and images into their individual frequency components in order to analyse, manipulate, and comprehend their spectral properties effectively. Telecommunications, audio and speech processing, image compression, pattern recognition, and many other fields have all undergone radical change as a result of the capacity to analyse signals and images in the frequency [1] domain.

In this study, we set out to present a thorough examination of harmonic analysis methods and the importance of these methods in signal and image processing applications. We will examine harmonic analysis' mathematical underpinnings, consider its uses in signal processing and picture processing, and talk about the difficulties and recent developments in this area [2].

The Fourier series and transform provide the basis of harmonic analysis. The Fourier series makes it possible to characterise periodic signals as the product of sinusoidal components, giving a clear-cut explanation of their frequency content. This idea is expanded to include non-periodic signals through the Fourier transform, enabling the representation of signals in the continuous frequency domain. The Fourier transform enables processes like filtering, modulation, and spectral analysis by providing useful information about the frequency content of the signal [3].

The Fourier[4] transform offers a global analysis of frequencies, but its temporal resolution is constrained. In order to overcome this drawback, wavelet transforms offer a multi-resolution signal analysis. By breaking down signals into time-frequency elements, they make it possible to analyse high- and low-frequency data at various scales. In image processing, wavelet-based transformations have proven especially useful since they allow for effective feature extraction, denoising, and compression while keeping crucial visual information.

The frequency[5] content of signals is represented in time using time-frequency analysis techniques like the short- time Fourier transform (STFT) and a spectrogram. These methods are commonly used in applications including speech processing, music evaluation, and biomedical signal processing. They capture the development of frequency components across time.

Different Application using Harmonic Analysis for Signal Processing:

The processing of audio and speech has been revolutionised by harmonic analysis. Fourier analysis in voice recognition enables the extraction of critical features such formants, pitch, and spectral features, which are essential for precise recognition. In order to produce speech that sounds natural, fourier-based approaches are also utilised in voice synthesis. Additionally, speech intelligibility is improved by using harmonic analysis in noise mitigation algorithms to extract speech from background noise [6].

In music analysis, harmonic analysis is crucial, helping with tasks like key detection, chord praise, and melody extraction. Harmonic analysis gives information about the harmonic framework and tonal substance of the music by dissecting musical information into their individual harmonic components. Moreover, to create realistic sounds that are musical and alter their timbre, Fourier-based techniques are used in music synthesis [7].

The Discrete Fourier Transformed (DFT) and wave transforms, two harmonic analysis methods, have made a substantial contribution to signal compression and decoding algorithms. The Fast Fourier Transformation (FFT), a well-known Fourier-based algorithm, is frequently used in music and image compression formats including MP3 and JPEG. Wavelet-based techniques, like JPEG2000, offer the best compression results by effectively expressing the frequency content of signals at various scales [8].

Techniques for harmonic analysis make it easier to enhance images and extract features. In order to improve certain frequency components of an image, such as reducing edges or smoothing textures, Fourier-based techniques are used. Image features can be extracted at many scales using wavelet-based techniques' multi-resolution analysis. Applications like texture analysis, recognising objects, and segmentation of images can all benefit greatly from this.

II. Related application Area

1. Spatial Data

The study used NOAA satellite series level 1B AVHRR satellite data. The data was divided into five spectral bands: thermal (ch.4-5, 10-12 m), near-infrared (ch.2, 0.83 m), visible (ch.1, 0.63 m), and near-infrared (ch.2, 0.83 m). The nominal spatial resolution of the AVHRR data was 1.1 km at nadir. The study concentrated on gathering NOAA/AVHRR data for the month of February between the years 1995 and 2005. The study made use of the AVHRR- Local Area Coverage (LAC) data type [11].

2. Auxiliary Information

Using ground truth data provided by BCCL (Bharat Coking Coal Limited), the suggested algorithm's results were verified. The precise locations of 30 hotspots in the Jharia region were included in this ground truth data. Co-registered "Google Earth" photos were also used to verify the correctness of the algorithm's results for classifying land cover [12].

III. Proposed Methodology

1. Pre-processing Data

Using commercially available software called ENVI, radiometric calibration and georeferencing of NOAA/AVHRR photos were carried out. The measurements in the initial two bands (bands 1 and 2) were converted from raw values to % reflectance during the calibration process. On the other hand, brightness temperature was calibrated into the data in bands 3, 4, and 5. This calibration process made sure that the picture values matched up with useful physical measures, allowing for proper data processing and interpretation.

2. Time-Series NOAA/AVHRR Data for Harmonic Analysis

The NOAA/AVHRR data has to be preprocessed in order to remove geometric distortions and guarantee radiometric correctness before beginning the harmonic analysis process. This process was essential to ensuring that the data was correctly calibrated and aligned, enabling precise harmonic analysis. Harmonic analysis techniques were then used on the time-series data after the data had been preprocessed. In order to do this, the NOAA/AVHRR sensor's complicated signals had to be broken down into their individual frequency components. Mathematical approaches like Fourier series and transforms, wave transforms, or time-frequency methods of analysis were used to carry out the decomposition [13].

In the Jharia region of Jharkhand, harmonic analysis of a 10-year time series of NOAA/AVHRR data was carried out to identify hotspots and categorise land cover. The research sought to make the most of the distinctive qualities of hotspot pixels and employ pertinent spectral bands for precise detection [14].

In AVHRR channels 1 and 2, it was believed[16] that hotspot pixels would have lower reflectance values than background pixels. Channel 2 reflectance was employed to get rid of any potential false alarms brought on by highly reflecting bare soil and rock. Additionally, it was believed that the Normalised Difference Vegetation Index (NDVI) was essential for identifying hotspots and classifying land cover. It was predicted that vegetation would be sparse in hotspot regions, resulting in lower NDVI values. These presumptions led to the use of AVHRR channel 1, channel 2, and NDVI data as the input for hotspot identification and land cover classification. Pixel by pixel, harmonic analysis was used to examine these spectral bands in the AVHRR time series data [18].

The method produced amplitude and phase images for each harmonic term by applying Fourier analysis to the full image. Significant changes in the data were discovered by examining the amplitudes and phases, which stand for the strength and timing of frequency components.

Since the [20] lower-frequency components of a dataset typically contain the majority of the variance, the harmonic analysis concentrated on isolating these prominent components. Patterns and trends regarding the prevalence of hotspots and the features of land cover could be discovered by analysing the amplitude and phase images. A wealth of knowledge regarding the distribution and temporal variations in hotspot intensity and land cover attributes was revealed by the produced amplitude and phase images. These photos were used as inputs for later image processing methods to properly identify land features and discover hotspots, such as thresholding or classifying algorithms [17].

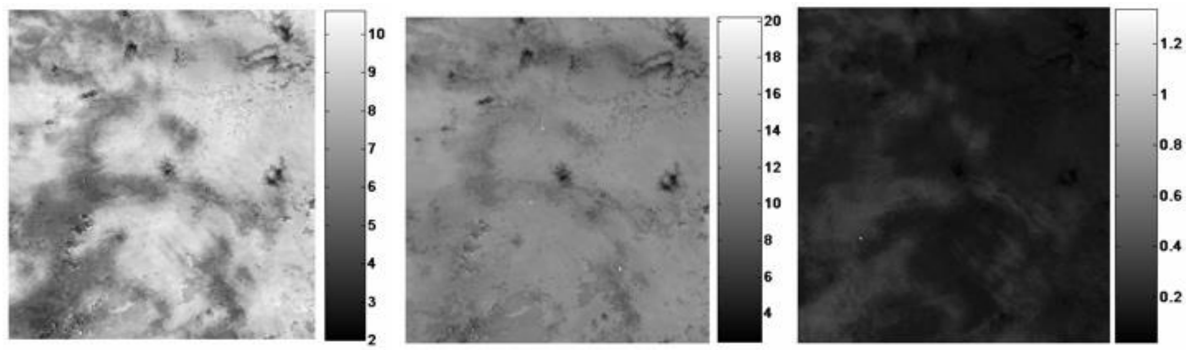

Figure 1: Schematic images of amplitude band 1, band 2and band 3

3. Utilising Image Processing Methods

For various geographical features, such as land, water, and medium forest land, the obtained amplitude images of the basic term corresponding to band 1, band 2, and NDVI exhibit varied properties. Successful land cover classification and hotspot detection are made possible by these distinctive properties. The retrieved amplitude images were processed using image-processing techniques to accomplish this goal, as shown in Figure 2. In the amplitude photographs, the medium forest land pixels in the study area exhibit particular traits. In the channel 1 amplitude image, they have low reflectance values, and in the NDVI amplitude image, they have high pixel values. In the resulting channel 1 amplitude image and NDVI amplitude image, the medium forest land pixels exhibit the lowest response and the highest response, respectively. They can be distinguished from the other land cover types based on these traits.

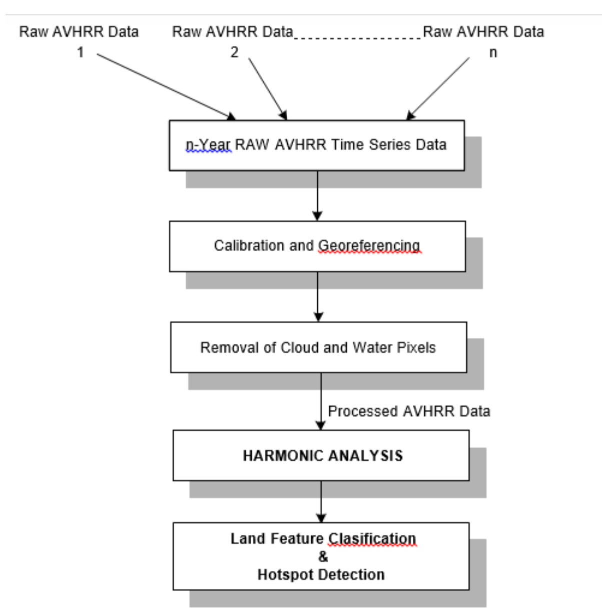

Figure 2: Proposed method for Harmonic Analysis with Application

Different land coverings, including land, water, and medium forest land, can be reliably categorised by using these segmentation approaches on the amplitude images. Additionally, segmented image analysis can be used to find hotspots in the images. Overall, the segmentation and categorization of land covers as well as the detection of hotspots are made possible by the image processing methods used to the extracted amplitude pictures. The system successfully distinguishes between various terrain features and correctly identifies regions of interest by utilising the distinctive properties seen in the amplitude images, helping to achieve the study's main objective.

The segmented pixels that are considered to be land and hotspots make up the final image after the segmentations previously discussed. Hotspot pixels can be distinguished from the background land pixels by their low reflectance values in AVHRR bands 1 and 2. The ground truth data provided by BCCL was used to compare the amplitude values of hotspot pixels to the background land pixels in the channel 1 and channel 2 resultant amplitude images, further confirming this characteristic.

The reliability and accuracy of hotspot detection are improved by combining the analysis of the amplitude values in the resultant amplitude images from channels 1 and 2 with the ground truth data. This method allows for the accurate identification and distinction of hotspots by taking into account the unique traits displayed by hotspot pixel in contrast to the background land pixels.

IV. Results and Discussion

As mentioned in Section III (C), the amplitude images were processed using image processing techniques to create the annotated categorised image shown in Figure 3. Four main categories have been used to categorise the image: water and cloud, intermediate forest land, hotspots, plus land pixels.

The categorization procedure makes use of the distinctive traits that various land covers display in the amplitude images. These features are used to precisely assign pixels to their relevant classes within the annotated image by using the proper algorithms or procedures. The classes include medium forest land, hotspots, water, and cloud, which are frequently combined due to their shared properties.

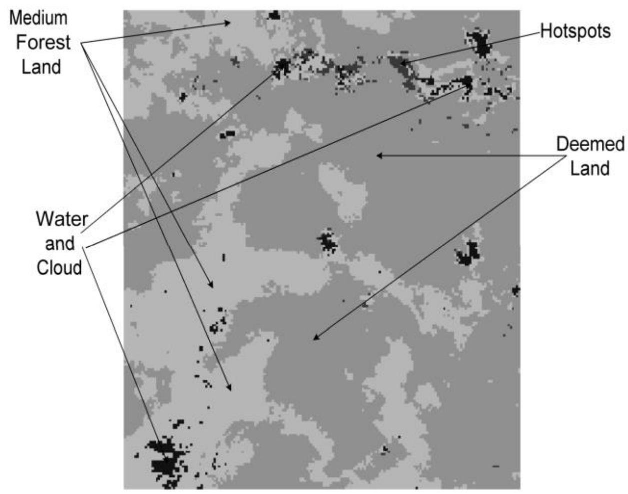

Figure 3: Classification result after AVHRR

The categorised image that results from the image processing methods used on the amplitude images gives a visual depiction of the classification of land cover that was accomplished. Using this graphic, one may analyse and comprehend how various land cover classes are distributed throughout the Jharia region as well as discover hotspots.

TABLE I. HOTSPOT CLASS CONFUSION MATRIX

Finding spot	**Projected Positive**	**Projected Negative**
Real Positive	24 (TP)	0.0 (FN)
Real Negative	311 (FP)	37741 (TN)

TABLE II. MEDIUM FOREST LAND CLASS CONFUSION MATRIX

Average Forest Terrestrial	**Projected Positive**	**Projected Negative**
Real Positive	10071 (TP)	0.0 (FN)
Real Negative	3026 (FP)	24929 (TN)

TABLE III. DEEMED LAND CLASS CONFUSION MATRIX

Supposed Terrestrial	**Projected Positive**	**Projected Negative**

Real Positive	24476 (TP)	3476 (FN)
Real Negative	15 (FP)	11410 (TN)

The confusion matrix is often used to compute classification accuracy, which is the percentage of samples that are properly identified out of all samples. It is determined by dividing the total number of samples by the sum of correctly classified samples (true positives and true negatives). A single metric reflecting the classification model's total accuracy in accurately classifying samples is produced by this calculation.

Accuracy = (Number of correctly classified samples) / (Total number of samples)

The suggested technique successfully identified all of the hotspots and correctly identified the various land covers in the region of interest. For the entire AVHRR classed image as well as for each class, the classification accuracy was calculated. The table's results demonstrate a high degree of accuracy.

The algorithm's overall classification accuracy was 91.04%, which is a noteworthy accomplishment. This high degree of accuracy shows that the algorithm successfully discriminated between various types of land cover and located the hotspots within the study area. The outcomes confirm the hotspot detection and land cover classification algorithms' efficacy and dependability.

V. Conclusion

Harmonic analysis has proven to be successful in a number of ways when used for signal and image processing applications. In the Jharia region of Jharkhand, the suggested method successfully detected hotspots and classified the land cover using harmonic analysis on a 10-year time series of NOAA/AVHRR data. The findings demonstrated that hotspot pixels have low reflectance values in AVHRR channels 1 and 2, and that NDVI, band 1, and band 2 amplitude pictures each have distinctive properties for various land features. This enabled the accurate identification of hotspots and the successful classification of land cover. Different land cover classes, such as water, land, and medium forest land, could be effectively discriminated using the segmentation techniques that were applied to the amplitude images. With an overall accuracy of 91.04%, the suggested algorithm also showed great classification accuracy. This demonstrates the algorithm's capability to correctly locate and categorise the relevant area, offering insightful data on the distribution of various land cover classes and hotspot locations. The reliable extraction of information from the AVHRR data was made possible by the use of harmonic analysis in conjunction with image processing techniques. The method demonstrated its sturdiness in the face of difficulties including cloud and water pixels as well as false alarms brought on by highly reflecting bare soil and rock. Harmonic analysis has shown promise in obtaining important information from time series satellite data through analysis for signal and picture processing applications. The suggested algorithm showed that it could efficiently identify hotspots and categorise land cover, which added to our understanding of land dynamics and helped us make decisions about how to manage land and monitor the environment. The accomplishment of this study demonstrates the significance of cutting-edge signal and image processing methods in realising the full potential of remote sensing data and prepares the way for further study and applications in the area of satellite data analysis.

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