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Enhanced Retrieve Land Surface Temperature from Mir Data Using Fuzzy Automatic Clustering Algorithm

T.Saranya MCA, M.Phil, P.Selvi M.Sc, M.Phil
Full Time Scholar, Vivekanandha college for women, Tiruchengode
Email:mtsaranya92@gmail.com
Assistant Professor, Vivekanandha college of Arts and Science for women, Tiruchengode
Email:selvisiva4@gmail.com

Abstract: *Land surface temperature (LST) is a solution variable in climatological and ecological studies. However, accurate measurements of LST over continents are not yet available for the whole globe. In this paper describes first reviews the state of the science of land surface temperature (LST) estimates from remote sensing platforms, models, and in situ approaches. Considering the suspicions, we review the current LST justification and estimate method. Then the requirements for LST products are specified, from the different user communities. Finally to identify the gaps between state of the science and the user community requirements, and discuss solutions to bridge these gaps. In this paper analysis a physics-based method to retrieve LST from the MODIS daytime MIR data in channels 22 (centered at 3.97 μm) and 23 (centered at 4.06 μm). On the basis of radiative transfer theory in the MIR region, a bidirectional reflectivity retrieval method. In this method to separate the reflected solar direct irradiance and the radiances emitted by the surface and atmosphere. The MIR spectral region (3–5 μm) has many advantages with respect to the TIR spectral region. MIR using the multispectral thermal imager and found that LST retrieved from MIR is only half as sensitive to errors in LSE as those retrieved from TIR. Consequently, it seems to be more appropriate to retrieve LST from MIR rather than TIR data. However, measurements in the MIR region at satellite altitudes during the daytime consist of a combination of both reflected radiance due to solar irradiance and emitted radiance from both the surface and the atmosphere.*

The reflected solar irradiance is on the same order of magnitude as the radiance emitted by the surface and the atmosphere, which makes it difficult to eliminate the solar effect on LST retrieval in the MIR. This is because the separation of solar irradiation from the total energy measured in the MIR requires not only accurate atmospheric information but also knowledge of the bidirectional reflectivity of the surface. The uncertainties in such information may lead to larger errors in the LST retrieved from MIR data. Therefore, there are currently few analysis of LST retrieval using MIR data. In this paper clustering method is implemented to process subsequences of time series data and identify land cover vary temperature measured as a function of time. Land cover change temperature measured is confirmed when successive subsequences that are extracted from one MODIS time series transitions from one cluster to another cluster and remains in the newly assigned cluster for the rest of the time series. The sequential sliding window designed to work on a subsequence of the time series to remove information from two spectral bands from the MODIS product.

Keywords: *Land Surface Temperature, MODIS, MIR, Solar irradiance, Radiative theory.*

I. Introduction

Digital image processing is the use of computer algorithms to achieve image dealing out on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing..

Image segmentation is the procedure of partitioning a digital image into several segments (sets of pixels, also known as super-pixels). The transformation of natural vegetation by practices such as deforestation, agricultural expansion, urbanization and natural disasters such as forest fires and floods has significant impacts on hydrology, ecosystems and climate. Coarse spatial resolution satellite data provide the regional, spatial, long-term and high temporal measurements for monitoring the earth surface.

Automated land cover change finding at district or global scales, using hyper-temporal, crude resolution satellite data has been a highly desired but elusive goal of environmental remote sensing. Hence, this project provides an automated land cover change detection method that uses coarse spatial resolution hyper-temporal earth observation satellite time series data. In addition, the details such as wild life movement, forest fire, deforestation and changes in vegetation nature are also covered. Based on the images collected at regular intervals, the comparison are made and analyzed. Using feature mining process that creates meaningful in order time series that can be analyzed and processed for modify detection. In addition, the Fuzzy C-Means approach is used to cluster the various types of sub image details. The method was evaluated on real and simulated land cover change examples and obtained more change detection accuracy.

II. Literature Survey

J. Hansen et al [1] describe the Goddard Institute for Space Studies (GISS) analysis of global surface temperature change, compare alternative analyses, and address questions about perception and reality of global warming. Satellite-experiential nightlights are used to identify measurement stations positioned in farthest darkness and adjust temperature trends of city and peri-urban stations for non-climatic factors, verifying that urban effects on analyzed global change are small. Because the GISS analysis combines available sea surface temperature records with meteorological station measurements, we test alternative choices for the ocean data, showing that global temperature change is sensitive to predictable temperature change in polar regions where clarification are limited.

Felix N. Kogan et al [2] describe the main goal of global agriculture and the grain sector is to feed 6 billion people. Frequent droughts causing grain shortages, economic disturbances, famine, and losses of life limit the ability to fulfill this goal. To mitigate drought consequences requires a sound early warning system. The National Oceanic and Atmospheric Administration (NOAA) has recently developed a new numerical method of drought detection and impact assessment from the NOAA operational environmental satellites. The method was tested during the past eight years, adjusted based on users' responses, validated against conventional data in 20 countries, including all major agricultural producers, and was accepted as a tool for the diagnosis of grain production.

Jose A. Sobrino et al [3] describe a SPECTRA (Surface Processes and Ecosystem Changes Through Response Analysis) is one of the core candidate missions which is being proposed for implementation in the European Space Agency (ESA) Earth Explorer program of research oriented missions. The scientific aim of the SPECTRA mission is to describe, understand, and model the role of earthly undergrowth in the global carbon cycle and its response to climate variability under the increasing pressure of human activity. The SPECTRA satellite will embark an optical hyperspectral payload covering the solar spectral range (0.4 to 2.4 mm) and thermal infrared region (10.3 to 12.3 mm).

III. Methodologies

A. Land Surface Emissivity (LSE)

Thermal emissivity e is the efficiency with which a surface emits the stored heat as thermal infrared (TIR) radiation. It is useful to indicates the composition of the radiating surface and necessary as a control in atmospheric and energy-balance models, since it must be known along with brightness temperature to establish the heat content of the surface. The first practical demonstration of multispectral TIR imaging for compositional mapping was from a NASA airborne scanner flown over Utah. Emissivity differs from wavelength to wavelength, just as reflectivity r does in the spectral region of reflected sunlight (0.4–2.5 mm). Emissivity is defined as

$$\boxed{\varepsilon(\lambda) = \frac{L(\lambda, T)}{B(\lambda, T)}}$$

Where L is the measured spectral radiance and B is the theoretical blackbody spectral radiance for a surface with a skin temperature T. B is given by Planck's law which, together with the basic physics of TIR radiative transfer, is discussed in the entry Land Surface Temperature (LST). Unlike T, which is a variable property of a surface controlled by the heating history and not directly by composition, e(l) is independent ofTand is a function directly of composition. Furthermore, e(l) in the TIR wavelengths(3–14 mm) responds to different aspects of composition than reflectivity r(l) at 0.4–2.5 mm. In general, r at wavelengths 0.4–2.5 mm is controlled by the amounts of iron oxides, chlorophyll, and water on the surface; e in the TIR is controlled more by the bond length of Si and O in silicate minerals.

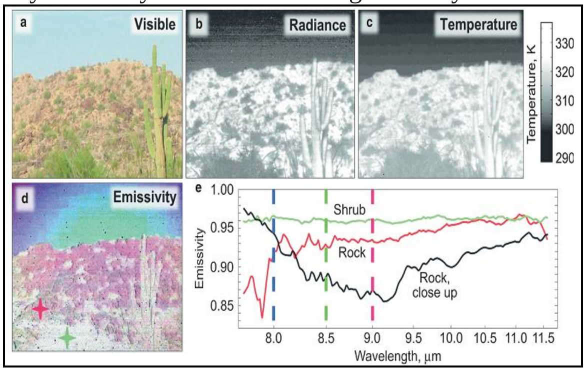
TIR spectroscopy is especially important because silicate minerals are the building blocks of the geologic surface of Earth, and their presence and amounts can be inferred only indirectly at shorter wavelengths. Thus TIR spectroscopy is complementary to spectroscopy of reflected sunlight. Good summaries of TIR spectroscopy and its significance in terms of surface composition.

Daytime and nighttime false-color composite images of spectral radiance from a sparsely vegetated part of Death Valley, California, enhanced using a decor relation contrast stretch. This stretch emphasizes the emissivity component of the signal, shown as color, and de-emphasizes the temperature, shown as dark/light intensity. In addition to composition, the daytime image gives a good sense of topography, because sunlit slopes are warmer than shadowed slopes. In the nighttime image, most temperature effects are subdued, and the image closely resembles the Land Surface Emissivity (LSE) alone.

Exceptions include standing water, which is cooler than the land during the day but warmer at night. Standing water (C) in the floor of Death Valley shows dark green in the daytime image but light pink in the nighttime image. Vegetation (A) appears dark in the daytime image, when it is cooling its canopy by evapotranspiration.

B. MIR IMAGE

In principle, this problem can be removed by increasing the number of images acquired for the same scene. For each n-channel image, after atmospheric compensation, there are n + 1 unknowns, but only n measurements; for two images of the same scene, there are n + 2 unknowns, but 2n measurements (assuming LST has changed but LSE has remained constant). Therefore, a two-channel image taken at two different times is deterministic. It is additionally necessary that the LST be significantly different between acquisitions.



Two-time, two-channel approach If well-registered multispectral day–night radiance measurements are available, it is possible to determine T and e uniquely (Watson, 1992a). Although this approach is esthetic, for most TIR data, the recovered temperatures and emissivities tend to be imprecise. For example, for image channels at 8 and 12 mm, day–night temperatures of 290 and 310 K, and for NEDT ¼ 0.3 K, recovered LST would have an uncertainty of 20 K. This arises because of the flat shape of the Planck curve in the spectral range around 300 K. By using an image channel in the 3–5 mm window, where the slope of the Planck function is steep, can improve the precision greatly and used the day– night algorithm to make a standard MODIS LST product.

1. Natural color.
2. MIR radiance at 9 mm.
3. Brightness temperature.
4. Emissivity (RGB ¼ 8, 8.5 and 9 mm, respectively).
5. Emissivity spectra measured with the TELOPS.

C. SPECTRAL-SHAPE SOLUTIONS

Although it is not possible to invert the modified Planck equation for both e and T without external constraints, it is possible to estimate spectral shape for e, at the expense of Tand of the amplitude of the recovered spectrum, that is, the recovered spectra are essentially normalized, so that only relative amplitudes (wavelength to wavelength) are known. This is nevertheless useful, since composition is generally determined from spectral shape, and not the absolute amplitudes.

Observed that ratios of spectrally adjacent channels i and j described spectral shape accurately, provided that T could be estimated even roughly

$$\boxed{\frac{\varepsilon_j}{\varepsilon_i} = \frac{L_j \lambda_i^5 \left(\exp\left(c_2/(\lambda_i T)\right) - 1\right)}{L_i \lambda_j^5 \left(\exp\left(c_2/(\lambda_j T)\right) - 1\right)}}$$

To calculate the e ratios, it is necessary to approximate the temperature T from the measured radiances Li and Lj. If e can be estimated with in 0.075 , the uncertainty in T is 5 K, and the e ratios can be estimated with an average error of 0.007 (this estimate does not include the effects of measurement error). Becker and Li (1990) proposed a similar approach they called the “temperature-independent spectral indices” (TISI) method. TISI begins with the observation (Slater, 1980) that Planck’s law may be represented by

$$B_k(T_s) = \alpha_k(T_o)T^{n_k(T_o)}$$

Where B is the spectral radiance in image channel k for a blackbody at temperature Ts and To is a reference temperature. Constants nk and αk are given by

$$n_k(T_o) = \frac{c_2}{\lambda_k T_o}\left(1 + \frac{1}{\exp(c_2/\lambda_k T_o) - 1}\right);$$
$$\alpha_k(T_o) = \frac{B_k(T_o)}{T_o^{n_k(T_o)}}$$
.

The land-leaving spectral radiance Lk, corrected for atmospheric absorption and path radiance but not down-welling spectral irradiance Lk.

$$L_k = \varepsilon_k \alpha_k T_s^{n_k} C_k; \quad C_k = 1 + \frac{(1-\varepsilon_k)L_k^{\downarrow}}{\varepsilon_k B_k(T_s)}$$

Where Ck is spatially variable and atmosphere specific . The TISI is found by rationing spectral radiances for image channels i and j Here ai is defined as ni 1 (and aj ¼ nj1), chosen to make Equation 6 independent of T. Since for a wide range of temperatures the C ratio is close to unity, TISI is then.

The ratio spectra are insensitive to temperature, for normal terrestrial ranges. The approaches are adaptable for most sensors

$$TISI_{i,j} = \left[\frac{L_i}{\alpha_i}\right]^{1/n_i}\left[\frac{L_j}{\alpha_j}\right]^{-1/n_j} = \frac{\varepsilon_i^{1/n_i}}{\varepsilon_j^{1/n_j}}\frac{C_i^{1/n_i}}{C_j^{1/n_j}} \approx \frac{\varepsilon_i^{1/n_i}}{\varepsilon_j^{1/n_j}}$$

.

D. ALPHA-RESIDUAL METHOD

The alpha-residual algorithm produces a relative emissivity spectrum that preserves spectral shape but, like the ratio methods, does not yield actual e or T values. The alpha residuals are calculated utilizing Wien's approximation of Planck's law, which neglects the "-1" term in the denominator. This makes it possible to linearize the approximation with logarithms, thereby separating λ and T

$$\frac{c_2}{T} \approx \lambda_j \ln(\varepsilon_j) - \lambda_j \ln(L_j) + \lambda_j \ln(c_1) - 5\lambda_j \ln(\lambda_j) - \lambda_j \ln(\pi).$$

Here c1 and c2 are the constants defined in Planck's law (Equation 1, Land Surface Temperature) and j is the image channel. Wien's approximation introduces a systematic error in e j of 1 % at 300 K and 10 mm wavelength. The next step is to calculate the means for the parameters of the linearized equation, summing over the n image channels:

$$\frac{c_2}{T} \approx \frac{1}{n}\sum_{j=1}^{n}\lambda_j \ln(\varepsilon_j) - \frac{5}{n}\sum_{j=1}^{n}\lambda_j \ln(\lambda_j) - \frac{1}{n}\sum_{j=1}^{n}\lambda_j \ln(L_j) + (\ln(c_1) - \ln(\pi))\frac{1}{n}\sum_{j=1}^{n}\lambda_j.$$

The residual is calculated by subtracting the mean from the individual channel values. Collecting terms, a set of n equations is generated relating ei to Li, independent of T.The components of the alpha-residual spectrum vary only with the measured radiances. They are defined as

$$\alpha_i \equiv \lambda_i ln(\varepsilon_i) - \mu_\alpha$$

Model approaches In this section, three algorithms distinguished by their model assumptions are described. The most specific requires that both a value ofe and the wavelength at which it occurs be known. The next requires only that the value be known. The third does not require the value of the emissivity to be known, only that the emissivity at two known wavelengths be the same The model emissivity (or reference channel) method assumes that the value of e for one of the image channel's ref is constant and known a priori, reducing the number of unknowns to the number of measurements. First, the temperature is estimated using

$$T = \frac{c_2}{\lambda_{ref}} \left(\ln \left(\frac{c_1 \varepsilon_{ref}}{\pi L_{ref} \lambda_{ref}^5} \right) + 1 \right)^{-1}$$

Scaling approaches Once relative spectra have been calculated, they can be calibrated to "absolute" emissivity provided a scaling factor is known. Applied to the ratio approach of this is basically the same as one of the model algorithms. However, scaling can also be done from empirical regression relating the shape of the emissivity spectrum to an absolute value at one wavelength. The regression is typically based on laboratory spectra of common scene components. More complex approaches also are possible: the first example given below combines the "two-channel, two-time," and TISI approaches to convert the relative TISI spectra to emissivities. The hybrid TISI approaches requires first that daytime and nighttime MIR and LWIR images be acquired and co-registered and that their TISI ratios be calculated. Essentially, there are four measurements (LMIR,day, LLWIR,day, LMIR,night, and LLWIR,night), four unknowns (eMIR, eLWIR), and one model assumption (the solar irradiance on the target). The MIR reflectivity is the complement of eMIR by Kirchhoff's law using widely separated image channels improves the precision of T and e recovery.

E. ALPHA-DERIVED EMISSIVITY (ADE) METHOD

The key innovation of the ADE approach is to utilize the empirical relationship between the average e and a measure of the spectral contrast or complexity in order to restore the amplitude to the alpha-residual spectrum.

IV. Performances Analysis

Area Wise Analysis

This table 5.1 shows the details of the image that is image taken from different locations or different area the size of the image in mega byte. The existing analysis and the proposed fuzzy automatic clustering are listed in this table.

Area wise image	Size of image (MB)	Existing analysis	Fuzzy Automatic Clustering
Water area	55	23	34
Land area	62	30	40
Agriculture area	74	42	50
Industrial area	82	52	63
Populated area	95	66	78

Table 5.1 Area Wise Analysis

The below chart shows that area wise analysis that is existing analysis and the fuzzy automatic clustering are shown in this chart.

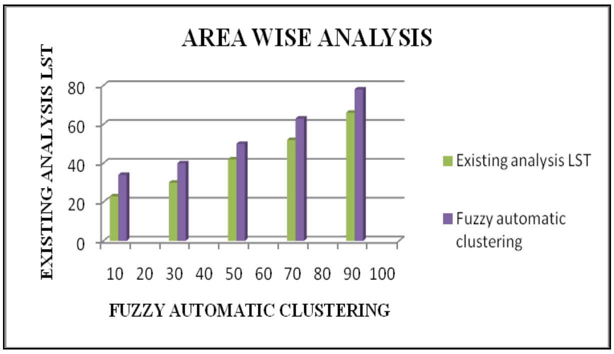


Fig 5.1 Area Wise Analysis

Time Wise Analysis

This table 5.2 shows the details of the image that is image taken from time to time that are represented in milliseconds. The existing analysis and the proposed fuzzy automatic clustering are listed in this table with their time analysis.

Area wise image	Size of image in MB	Existing analysis in m.sec	Fuzzy automatic clustering in m.sec
Water area	55	0.011	0.009
Land area	62	0.026	0.019
Agriculture area	74	0.035	0.022
Industrial area	82	0.046	0.036
Populated area	95	0.054	0.044

Table 5.2 Time Wise Analysis

The below chart shows that time wise analysis that is existing analysis and the fuzzy automatic clustering are shown in this chart.

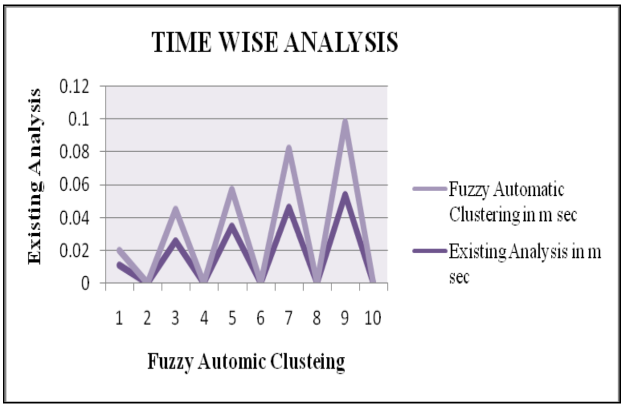


Fig 5.2 Time Wise Analysis

V. Conclusion And Future Enhancement

In this proposed system the land area and the water area regions are separated using the MODIS Satellite Data the specific area image is been selected and the temperature in that area is been identified. The previous study doesn't concentrate in the specific region they consider the entire region so that the accuracy of the estimation will be the major problem in finding the temperature. The proposed system concentrate in finding the specified area problem by using the MODIS image in that a region of the place is selected and that is separated as the land and the water area and the temperature is been noted.

On the basis of radiative transfer theory in the MIR region, a bidirectional reflectivity retrieval method was used to separate the reflected solar direct irradiance and the radiances emitted by the surface and atmosphere. A kernel-driven model was proposed to describe the non-Lambertian reflective behavior of the land surface and to accordingly determine the directional emissivity if there were more than three bidirectional reflectances available with different angular configurations on several consecutive days. The results showed that the bias and RMSE between the LSTs retrieved from MODIS daytime MIR data and those calculated using in situ measurements, at the time of the MODIS images. The proposed method could be used to accurately retrieve LST from MODIS daytime MIR data. The proposed system only concentrates in finding the changes in the agricultural area only but this should be taken for the consideration. That is the land area changes will be happened in the wild life costal area and also in the sea shore areas. This proposed system can be extended in the all the regions to intimate the land temperature variations. It is also includes mountains and the hill stations regarding sand slope like nature disasters to the nearer people. This identification duration can be altered and the satellite image taken can also be altered in this future plan. Instead of taking the image in finding the changes the video that is recorded in the satellite may taken for the analysis.

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