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Survey of Retrieve Land Surface Temperature from Daytime Mid-Infrared Data Framework

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Abstract: Land surface temperature (LST) is a key variable in climatic and ecological studies. However, accurate measurements of LST over continents are not yet available for the whole globe. This thesis 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 Land Surface Temperature confirmation and estimation method. Then the requirements for LST products are specified, from the different user communities. 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). 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. In this paper proposed clustering method is implemented to process subsequences of time series data and detects land cover change temperature measured as a function of time. Land cover change temperature measured is declared when consecutive 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 temporal sliding window designed to operate on a subsequence of the time series to extract information from two spectral bands from the MODIS product.

Keywords: Land Surface Temperature (LST), Mid-Infrared (MIR), Modis, Image Segmentation, Fuzzy c-means clustering.

I. INTRODUCTION

Digital image processing is the make use of of computer algorithms to perform image processing 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 lot wider range of algorithms to be applied to the input data and can avoid troubles such as the build-up of noise and signal distortion through processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems.

Image segmentation is the process of partitioning a digital image into several segments (sets of pixels, also recognized as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.
Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More particularly, image segmentation is the practice of passing on a tag to each pixel in an image such that pixels with the similar label distribute certain uniqueness.

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 detection at regional or global scales, using hyper-temporal, coarse 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.

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Based on the images collected at regular intervals, the comparison are made and analyzed. Using feature extraction process that creates meaningful sequential time series that can be analyzed and processed for change 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. Now, drought can be detected 4–6 weeks earlier than before, outlined more accurately, and the impact on grain reduction can be predicted long in advance of harvest, which is most vital for global food security and trade. This paper addresses all these issues and also discusses ENSO impacts on agriculture.

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). This paper is focused on the land surface temperature retrieval from SPECTRA thermal infrared data. In the first part of the paper, generalized single-channel and split-window methods are discussed and compared, showing that single-channel methods provide similar or better results than split-window methods for low atmospheric water vapor content, whereas split-window methods always provide better results for high atmospheric water vapor content. In the second part of the paper, split-window and dual-angle algorithms have been developed for SPECTRA thermal channels.

Zhengming Wan et al [4] demonstrate about a universal split-window method for retrieving LST from AVHRR and MODIS data. Precise radiative transfer simulations show that the coefficients in the split-window algorithm for LST must vary with the viewing angle, if we are to achieve a LST accuracy of about 1 K for the whole scan swath range (USE‘ from nadir) and for the ranges of surface temperature and atmospheric conditions over land, which are much wider than those over oceans. We obtain these coefficients from regression analysis of radiative transfer simulations, and we analyze sensitivity and error over wide ranges of surface temperature and emissivity and atmospheric water vapor abundance and temperature. Sim- ulations show that when full of environment water breath increases and viewing angle is larger than 45‘, it is necessary to optimize the split-window method by separating the ranges of the full of atmosphere water breath, lower boundary temperature, and the outside temperature into obedient subranges.

Juan C. Jimenez-Munoz et al [5] describe a algorithms to retrieve land surface temperature from at-sensor and land surface emissivity data. These algorithms have been specified for different thermal sensors on board satellites, i.e., the algorithm used for one thermal sensor (or a combination of thermal sensors) cannot be used for other thermal sensor. The main goal of this paper is to propose a generalized single-channel algorithm that only uses the total special water vapour content and the channel valuable wavelength (assuming that emissivity is known), and can be applied to thermal sensors characterized with a FWHM (Full-Width Half-Maximum) of around 1 mm actually functioning on board satellites. The main advantage of this algorithm compared with the other single channel methods is that in-situ radio soundings or effective mean atmospheric temperature values are not needed, whereas the main advantage of this algorithm compared with split-window and dual-angle methods is that it can be applied to different thermal sensors using the same equation and coefficients.

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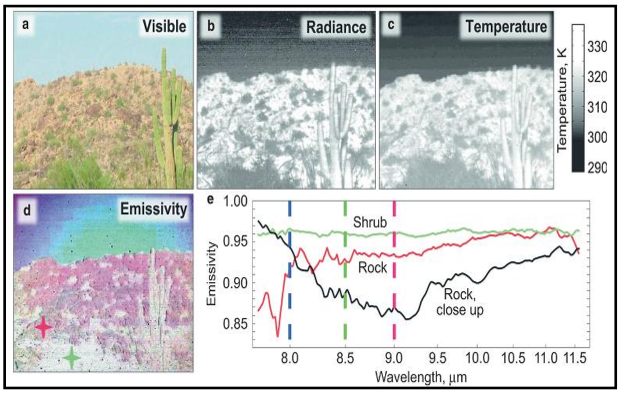
III. METHODOLOGIES

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.

A. 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 T and 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

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

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

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

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

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

B. 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.

Note that ki contains only terms which do not include the measured spectral radiances, Li, and hence may be calculated from the constants. Although dependency on T has been eliminated, it has been replaced by the unknown ma, related to the mean emissivity, such that the total number of unknowns is unchanged. The components of the alpha-residual spectrum vary only with the measured radiances. They are defined as

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

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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

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

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.

C. 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. The regression is based on the observation that, for a blackbody, the mean emissivity is unity and the spectral variance is zero. For minerals with restrahlen bands or other emissivity features, the variance is greater than zero and, of course, the mean is less than unity. In use, the mean is predicted from the variance, which is calculated from the measured radiances

IV. CONCLUSION

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 MRI 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.

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