A Probabilistic Model for Stratospheric Soil-Independent Dust Aerosol Detection

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Abstract: We present a simple probabilistic model for dust aerosol detection, analysing MODIS $11.3\mu m$ and $12.02\mu m$ thermal emissive bands. We introduce a dust aerosol probabilistic visualization, and a feasible extension to classification.

OCIS codes: (280.1100) Aerosol detection; (100.2960) Image analysis

1. Introduction

Dust aerosols can be carried across Earth's atmosphere arising dust aerosol air pollution problems. A recent study [1] shows correlation between dust aerosol air pollution and lung cancer. Several methods for dust aerosol detection and visualization exist, however, questions regarding the detection and feature extraction process remain open [2]. In the literature we can find the dust aerosol analysis problem addressed from different perspectives. According to the geophysical perspective dust aerosols can be visually inspected using satellite infrared bands [3, 4]. Also in [5, 6], the authors show how to improve dust storms visualization. However, there are no generalized soil-independent dust aerosol detection methods. Different aerosols can be found in the atmosphere, making dust aerosol modeling very difficult. Moreover, dust aerosol optical thickness models vary depending on regional soil type and minerals. Therefore, we propose the MODIS infrared thermal emissive bands 31 and 32 usage, from both Terra and Aqua satellites. We demonstrate that these bands provide sufficient characteristic information to identify dust aerosols. Then, after recovering MODIS Level 1B data and performing fundamental statistical analysis, we found that a Gaussian function best fitted its distribution. Thus, we performed a Gaussian model parameter estimation, generating a dust aerosol probabilistic visualization. In the following sections we describe a multispectral data analysis; from this analysis we build a simple probabilistic model. Then, we present the results and draw conclusions.

2. Stratospheric Dust Aerosol Statistical Distribution

Let X be a discrete real valued random variable associated to the thermal emissive measurements universe $G \in \Re$. Let $X_1, X_2, ..., X_N$ be a set of N random variables associated to thermal emissive spectral bands. MODIS integer scaled spectral band measurements can be recovered to its original units $(W/m^2/\mu m/sr)$ using the formula:

$$\hat{X} = \alpha(\beta - \gamma), \tag{1}$$

where α are the radiance scales, β are the radiance offsets, and γ are the scaled intensities or raw data; these three parameters are given in MODIS Level 1B data sets. Now, let a multispectral vector F be defined as

$$F = \hat{X_1}, \hat{X_2}, ..., \hat{X_N}, \tag{2}$$

where the elements of F are recovered multispectral bands using Eq. (1).
If we study the aerosols properties using F, we will understand the aberrant nature of the problem. Consider February 19th 2004's dust storm, and analyze a $C \in F$ scatter plot, for $C = \{$dust storm, smoke aerosol, cloud aerosol, everything else (background)$\}$. Figure 1 a) exemplifies the case of a band 31 and 32 2D scatter plot; clearly the C aerosol spectral properties are very similar. Now, if we study only the dust aerosol frequency histogram, we can indeed investigate its statistical distribution. Consider the MODIS recovered band 31, and examine at the histogram shown in Figure 1 b); if we try histogram fitting using known distributions, it can be followed that the Gaussian-based distributions perform a better fit. Numerically, for all F dimensions, a purely Gaussian function best approximate the dust aerosol distribution. For dust aerosol histogram approximation, we considered approximately 75 million data samples. These data samples were extracted from 31 dust aerosol observation cases [7]. A well known semi-automatic visual segmentation algorithm performed the dust aerosol identification. In the following section we summarize a dust aerosol detection probabilistic model derived using multispectral data linear combinations.

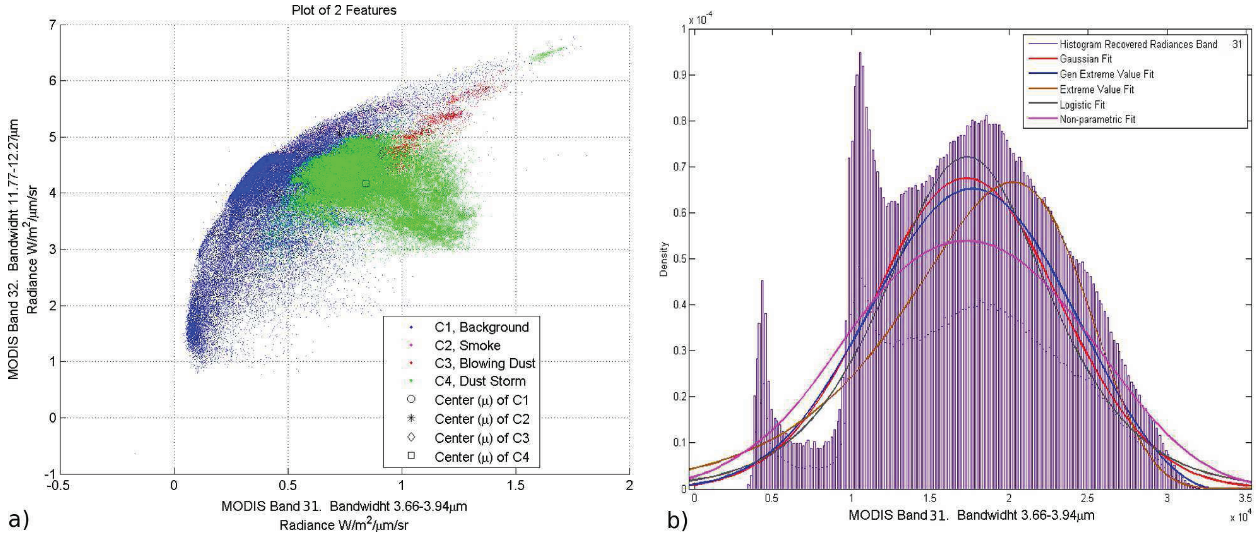


Fig. 1. Figure 1. a) shows a MODIS bands 31 vs 32 scatter plot. While b) shows the dust aerosol frequency histogram for band 31.

3. Probabilistic Modeling as a Two Random Variable Linear Combination

Let $f_X(X = x)$ denote the the spectral data probability density function with value equal to x. We are interested on displaying the dust aerosol observation probability, provided a MODIS data linear combination. More specifically, a two random variables difference, corresponding to MODIS recovered infrared bands 31, and 32. As shown previously, dust aerosol spectral properties follow a Gaussian distribution, therefore, it follows that Gaussian random variable linear combinations results also in a Gaussian distribution. We pose the problem introducing a new variable Z as a function of two random variables:

$$Z = \hat{X}_{32} - \hat{X}_{31}. \tag{3}$$

The random variable Z follows a Gaussian PDF with sample mean μ_Z, and sample variance σ_Z^2. That is $f_Z(Z = z) = N(\mu_Z, \sigma_Z^2)$. We used unbiased estimators to obtain the parameters set (μ_Z,σ_Z^2). Thus, the proposed detection method obtains the dust aerosol probability in Z, evaluating $f_Z(Z = z)$.

3.1 An Extension to Segmentation and Classification

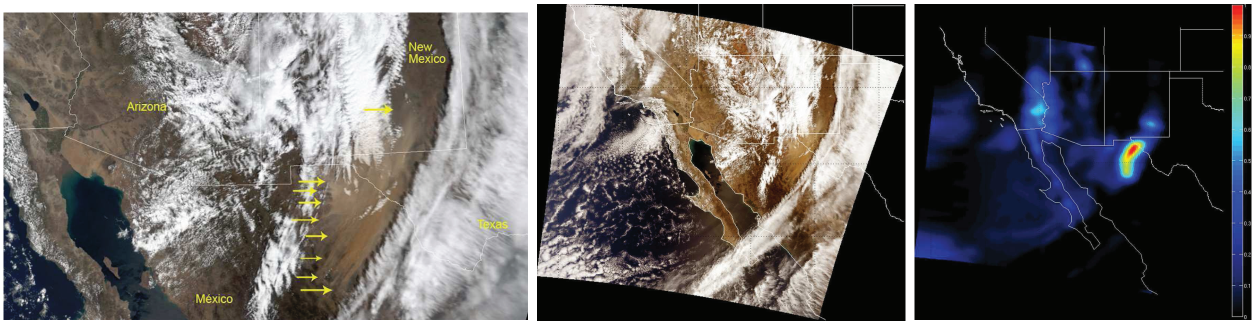
Our probabilistic model has a unique advantage: it can easily be translated to a classification or segmentation problem. This segmentation or classification can be achieved by thresholding $f_Z(Z = z)$'s output, up to a desired confidence interval. We pose the classification problem using the following decision rule

$$\begin{array}{lcl} z \text{ is dust} & \text{if} & f_Z(Z = z) \;>\; \tau \;\;,\;\; 0 \leq \tau \leq 1 \\ z \text{ is background} & & \text{otherwise} \end{array} \tag{4}$$

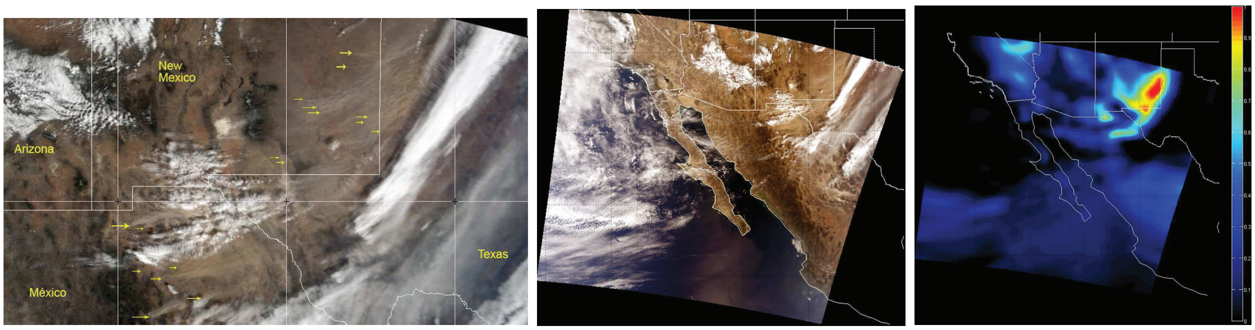
where τ denotes the threshold.

4. Implementation Results

The probabilistic model implementation described in previous sections, inculcates the following process: First, receive as input multispectral raw data, MODIS Level 1B thermal emissive bands 31 and 32. Second, original radiances are recovered using Eq. (1). Third, recovered bands 31 and 32 are subtracted producing Z as in Eq. (3). Fourth, a Gaussian function evaluates Z with parameters (μ_Z,σ_Z^2), obtaining the dust aerosol probability. Fig. 2 shows results of two known events. April 6th 2001's dust storm shown in Fig. 2 a-b, produces the probabilistic map shown in Fig. 2 c. Similarly, February 19th 2004's dust storm shown in Fig. 2 d-e, produces the results shown in Fig. 2 f. As can be seen, our model accurately detected the dust storm aerosols. Moreover, it provides dust transport information which can be associated to low probability detections. The model has been tested in 36 world wide events providing satisfactory results either over land or ocean.



(a) True color image. (b) Satellite scan. (c) Dust probability.



(d) True color image. (e) Satellite scan. (f) Dust probability.

Fig. 2. a)-c) Shows April 6th 2001's dust storm; while in d)-f) February 19th 2004's dust storm.

5. Conclusions

The dust aerosol detection problem has been addressed in this paper. We have modeled a probabilistic approach for dust aerosol detection, and explained the extension to segmentation and classification. The model's germane relies in the dust aerosols presence probability estimation, given MODIS Level 1B data. We develop our model based on MODIS recovered data linear combinations. To the authors best knowledge, the presented visualization model is the first in its kind since it can actually perform detection over land and ocean disregarding the dust aerosol type. Moreover, the proposed probabilistic model fits in near real-time applications, such as: direct broadcast, rapid response analysis, emergency alerts, etc. The work reported in this document make less burdensome dust aerosol analysis, since the model detects dust aerosols up to a 1 km resolution. This represents an improvement over methods based on the Aerosol Optical Thickness index (AOT) which have resolution paucity and a two day generation delay.

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