BACKGROUND SUBTRACTION AND DUST STORM DETECTION

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ABSTRACT

Mineral dust aerosols can influence the Earth's climate system to a significant degree and have a strong effect on terrestrial and oceanic biogeochemical cycles. As one step in quantifying dust sources, sinks, and transport, this paper seeks to quantify the presence of dust storms in the Sahara desert, which is the most active worldwide source of dust.

Our work is based on the SEVIRI infrared imager onboard the geostationary Meteosat-8 satellite, providing three separate channels at a 3km by 3km resolution. The significant challenge is that the infrared channels are highly influenced by the presence of water clouds and surface temperatures, which complicate the identification of dust-cloud anomalies. This paper develops a method of spatio-temporal background estimation from sparse data as a way of recovering dust images and presents results on real data.

***Index Terms*—** Background Estimation, Dust Cloud Identification

1. INTRODUCTION

There exist a great many significant transport phenomena between the earth's surface and its atmosphere. Of all of the aerosols in the atmosphere, the largest contribution arises from desert dust and sand [1], and of that more than half comes from deserts in northern Africa. The annual quantity of sand transport into the atmosphere is a staggering 1000 to 5000 Megatons, with the significant range in these values a clear indication of the variability from year to year, but also an absence of accurate data analysis [2].

The transport of desert sand and dust is important from a wide variety of contexts — dust may interfere with commerce and air travel, and it is possible for the dust to be swept higher into the atmosphere for a period of weeks, with consequent influences on the broader climate. The transport of minerals, primarily iron, in dust clouds from the Sahara to the Atlantic ocean, forms a significant nutrient transport with influence on plankton growth and carbon-dioxide uptake.

The possibility, therefore, for near real-time identification and prediction of dust storms from satellite imagery is of great interest. Recently, dust detection has been address based on a probabilistic analysis of multispectral images [3, 4]. In our case, the SEVIRI infrared imager on-board the geostationary Meteosat-8 satellite provides images, all day, at 15-minute intervals. With the data volumes overwhelming any possibility of human inspection, an automated approach is clearly needed. However, as can be seen from Figure 1(a), northern Africa is far from being a uniform field of sand, and the infrared images suffer from a wide range of effects: the presence of clouds, surface warming, and significant variations due to topography. Clearly what is needed is some way to correct for the space- and time-varying background.

Background subtraction is the fundamental process of automatically or semi-automatically separating foreground objects from the background. Recursive techniques proceed frame by frame, such as the approximated median filter, the Mixture of Gaussians, and the Kalman filter and its variants. Non-recursive techniques [5] include frame differencing [6], median filtering, linear predictive filtering, and non-parametric models. Our approach is non-recursive, a noncausal approach to background estimation.

However, in contrast to many background estimation problems in computer vision, which normally have a static background or a slowly-changing one, the infrared "background" in Africa exhibits wide daily swings. Superimposed on this variation are water clouds which can occupy a substantial fraction of the image, and themselves have a varying infrared signature depending on time and location. The key challenge in this research is the estimation of a time-varying background having spatial features and texture [7, 8], but subject to substantial occlusion from water and dust clouds.

2. PROBLEM FORMULATION AND RESULTS

We are given a sequence of images I_t^c at time t and in infrared channel c. We model the image as

$$I_t^c = B_t^c + W_t^c + D_t^c + N_t^c \tag{1}$$

such that the image is a sum of background (surface) effects B, water (clouds) W, dust D, and noise N. From the image–background residual $I^c - B^c$ we wish to infer the dust signature image D_t over time, such that D is some measure of dust concentration or suspended mass.

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The background B is assumed to be influenced by a temporal phenomenon (driven by the sun), which is spatially smooth, and a surface topographic component, which has no spatial smoothness but is temporally constant. By separating the temporal and spatial components of the problem in this way, an effective temporal background can be estimated given sparse data. Our fundamental premise regarding the spatio-temporal time scales of the background is therefore

- The background has a temporal variation P_t which is highly smooth spatially,
- The background has a spatial variation M which is fixed temporally,

such that $B_t = M \cdot P_t$. From this formulation we have developed a spatial-temporal background estimation algorithm.

Because our observed images are essentially the background, with deviations due to water clouds, dust, and noise, given the water/dust cloud indicator functions I^W, I^D, those regions free of cloud artifacts, that is, those x, y, t where

$$C_{x,y,t} = I^W_{x,y,t} + I^D_{x,y,t} = 0 \tag{2}$$

give us an initial background estimate,

$$\hat{B}^c_{x,y,t} = \begin{cases} \text{NaN} & C_{x,y,t} = 1 \\ I^c_{x,y,t} & C_{x,y,t} = 0 \end{cases} \tag{3}$$

where NaN (not-a-number) indicates the presence of cloud, meaning that the distribution of actual background values in $\hat{B}$ may be highly sparse.

Jointly estimating dense maps for M and P is very difficult, so based on their respective spatio-temporal properties we are proposing an alternating iteration algorithm to estimate the background.

Since M is temporally fixed, our best estimate is the mean over B:

$$M^c(1) = \text{mean}_t\, \hat{B}^c_t \tag{4}$$

where the mean is understood to be taken only over real values, not NaN.

Next, the temporal variations not accounted for in M must be reflected in P:

$$P^c_t(1) = \hat{B}^c_t / M^c(1) \tag{5}$$

where the division is element-by-element. Crucially, however, nothing has been asserted regarding the spatial smoothness of P, which forms the basis for the spectral separability between M and P. Therefore (5) is actually

$$P^c_t(1) = \text{Smooth}\left(\hat{B}^c_t / M^c(1)\right) \tag{6}$$

where the smoothing ignores NaN, and is normalized to give an unbiased smoothing regardless of NaN density.

In principle, this modified P should allow for a revised estimate of M, so we are left with the iteration

$$B^c(i) = P^c_t(i-1) \cdot M^c_t(i-1) \tag{7}$$

$$M^c(i) = mean_t\, \hat{B}^c_t(i) \tag{8}$$

$$P^c_t(i) = \text{Smooth}\left(\frac{\hat{B}^t_c(i)}{M^t_c(i)}\right) \tag{9}$$

Data were acquired from the SEVIRI infrared imager onboard the geostationary Meteosat-8 satellite [1]. The results are shown for a two-day period of data, with frames in each of the three channels taken 15 minutes apart.

3. EXPERIMENTAL

To validate the effectiveness of our background subtraction approach we have undertaken both visual and quantitative validations.

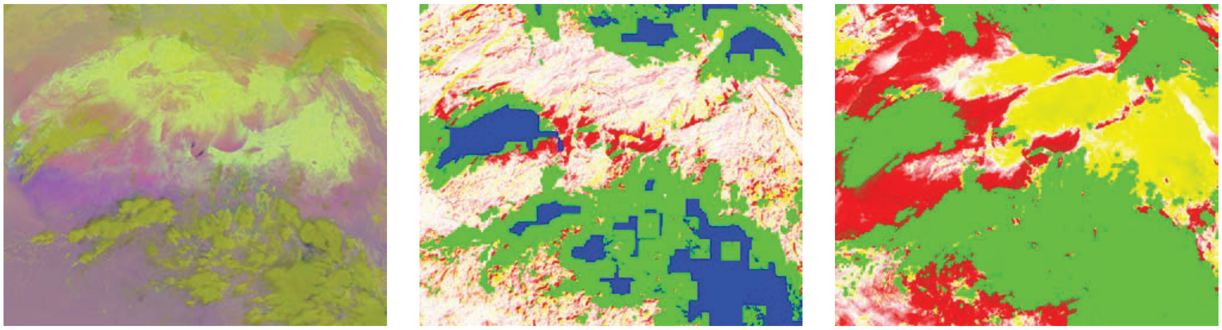
There are a variety of possible backgrounds to compute from our data: a point-wise average or spatial smoothing, using all of the data or avoiding water and dust cloud points, and averaging over all time or for only a subset of the measured period. Of these permutations, our proposed approach is water- and dust-cloud avoiding, involving spatial smoothing, and flexibly averaging over a period of time. Figure 1 illustrates one example of our method. A simple background produced by temporal averaging leads to a significant leakage of water and dust signal into the background, and the single background image so produced is static and unable to reflect the very strong daily variations in temperature.

Even a background which ignores the segmented water and dust components and is free of signal leakage remains susceptible to large biases, because clouds obscure different parts of the background at different times of day.

Our proposed method leads to a temporal background, following the daily heating / cooling cycle, and minimizing the influence of clouds. The difference image in Figures 1(b) still contains elements of the background, especially high-contrast topographical features (coastlines), but also clearly shows the dust residual, far more so than the difference to the averaged image in Figure 1(c).

For quantitative validation, a semi-automatic approach was also used to test segmentation and background estimation:

1. Manually choose 30-50 points in cloud-free, water-cloud and dust-cloud regions in every frame.
2. Compare with segmented results to determine classification accuracy.
3. Calculate pixel-wise absolute differences between original image and estimated backgrounds as a function of pixel class.



(a) Infrared Image (b) Proposed Background Estimation (c) Point-wise Averages

Image - Background differences

(Green/Blue = Cloud, Red/White/Yellow = pos. / zero / neg. differences)

Fig. 1. Given a sequence of infrared images (a), a background can be estimated. If the background is estimated, as proposed, from non-cloud, non-dust pixels then the image-background difference (b) reveals the presence of dust clouds (red), but if point-wise averages are used to find the background, then the image-background difference (c) has significant contamination.

For each frame at time t we have n_t^j ground-truth points for class j (cloud-free, water-cloud and dust-cloud).

We can calculate a mean absolute difference as

$$D_c^j = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{i=1}^{n_t^j} |I_t^c(x_i, y_i) - B_t^c(x_i, y_i)|}{n_t^j}. \qquad (10)$$

Given ground-truth locations of cloud-free and dust-cloud, we can assess the effectiveness of a given background-estimation approach by examining D. In particular, cloud-free areas should, ideally, have D near zero, and dust-cloud areas should have large D, reflecting a strong image-background residual. Our initial tests confirm these expectations, and show our proposed approach to separate clear/dust in D more effectively than any other method tried.

4. CONCLUSIONS

We have proposed a time-varying approach to background estimation, particularly applicable to daily cycles in remotely sensed imagery. The method estimates the temporal background, following the daily heating / cooling cycle, and minimizing the influence of clouds.

Future work will focus on more extensive ground-truth validation and tests on additional time series.

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