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, sink, and transport, this paper seeks to quantify the presence of dust storms in the Sahara desert, the most active worldwide source of dust.

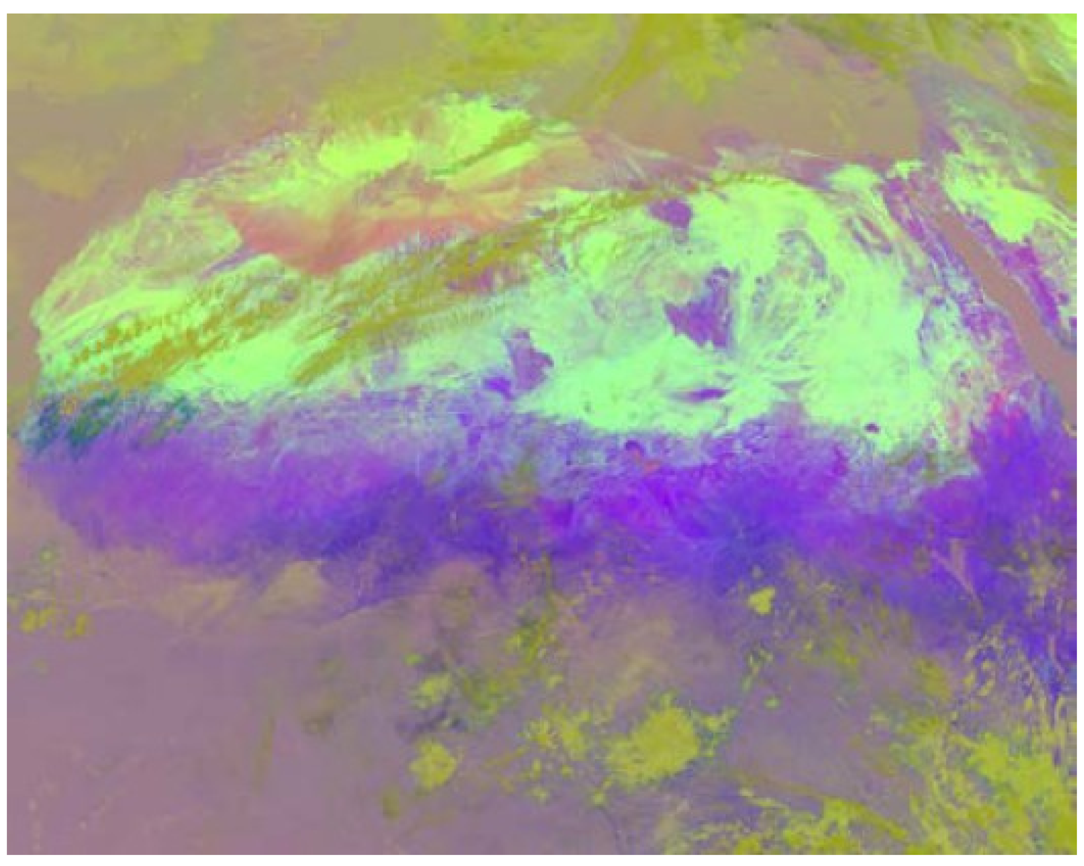

Figure 1. A false-color image of unprocessed infrared data. Green to blue are the surface response, with spatial variations due to the surface. The extensive tan-brown regions are water clouds. The dust cloud, which interests us, is the red region in the upper-left of the image.

Problem and Objective

- As can be seen from Figure 1, 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.
- 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. The key challenge here is the estimation of a time-varying background having spatial features and texture, but subject to substantial occlusion from water and dust clouds.
- Therefore, real-time identification and prediction of dust storms from satellite imagery is of great interest.

Problem Formulation:

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

$$I_t^c = B_t^c + W_t^c + D_t^c + N_t^c$$

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 we wish to infer the dust signature D over time, such that D is some measure of dust concentration or suspended mass.

Proposed Method:

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:

1) The background has a spatial variation M which is fixed temporally.

2) The background has a temporal variation which is highly smooth spatially,

From this premise, 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

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

give us an initial background estimate,

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

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:

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

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

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

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 the previous equation is actually:

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

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

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

$$B^c(i) = P^c_t(i-1) \cdot M^c_t(i-1)$$

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

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

Experimental Results:

- To validate the effectiveness of our background subtraction approach we have undertaken both visual and quantitative validations.
- 30-50 points were chosen in cloud-free, water-cloud and dust-cloud regions in every frame. Compare with segmented results to determine classification accuracy.
- Calculate pixel-wise absolute differences between original image and estimated backgrounds as a function of pixel class.
- Figure 2 shows a confusion matrix of our segmentation result.
- Figures 3,4,5, and 6 illustrate 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.

Classified as

	Clear	Water	Dust
Clear	99.5%	0.4%	0.1%
Water	0.0%	99.9%	0.0%
Dust	21.5%	2.3%	77.6%

Figure 2. A confusion matrix demonstrating the classification results based on manually chosen ground truth points.

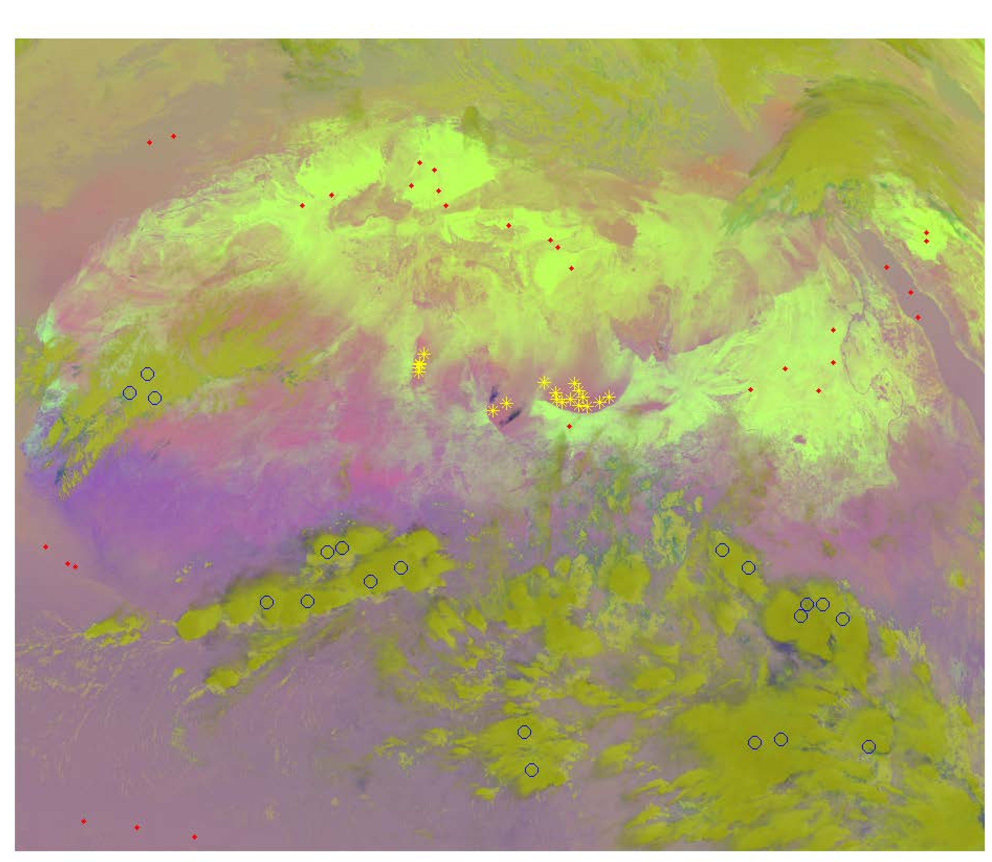

Figure 3. Manual ground truth points: Water—blue circle, dust—yellow star, clear—red points.

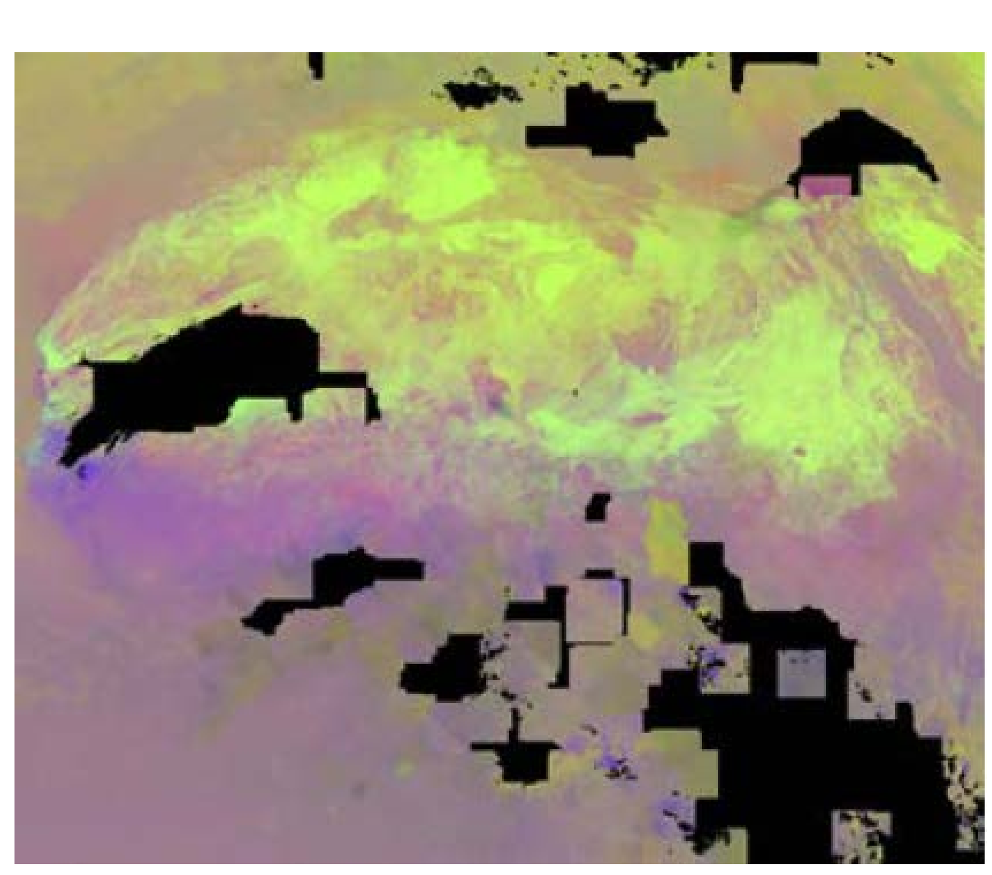

Figure 4. The background generated by our proposed method (black regions have no data).

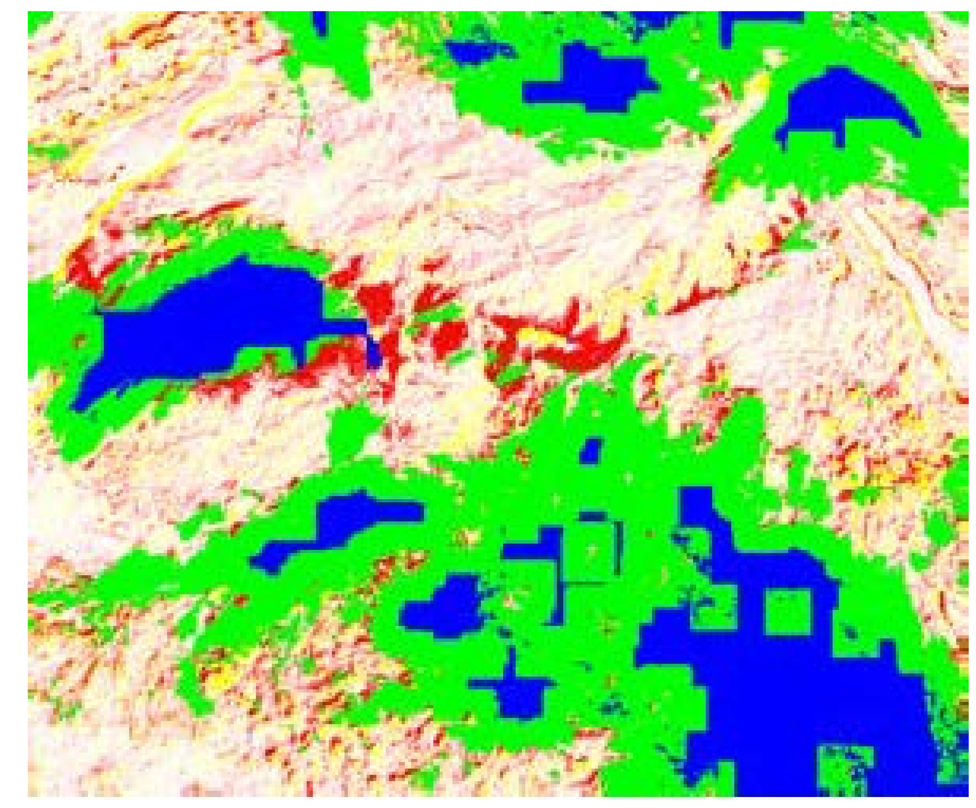

Figure 5. Difference between original image and estimated background generated by the proposed method.

Green/Blue = Cloud,

Red/White/Yellow = pos. / zero / neg. differences

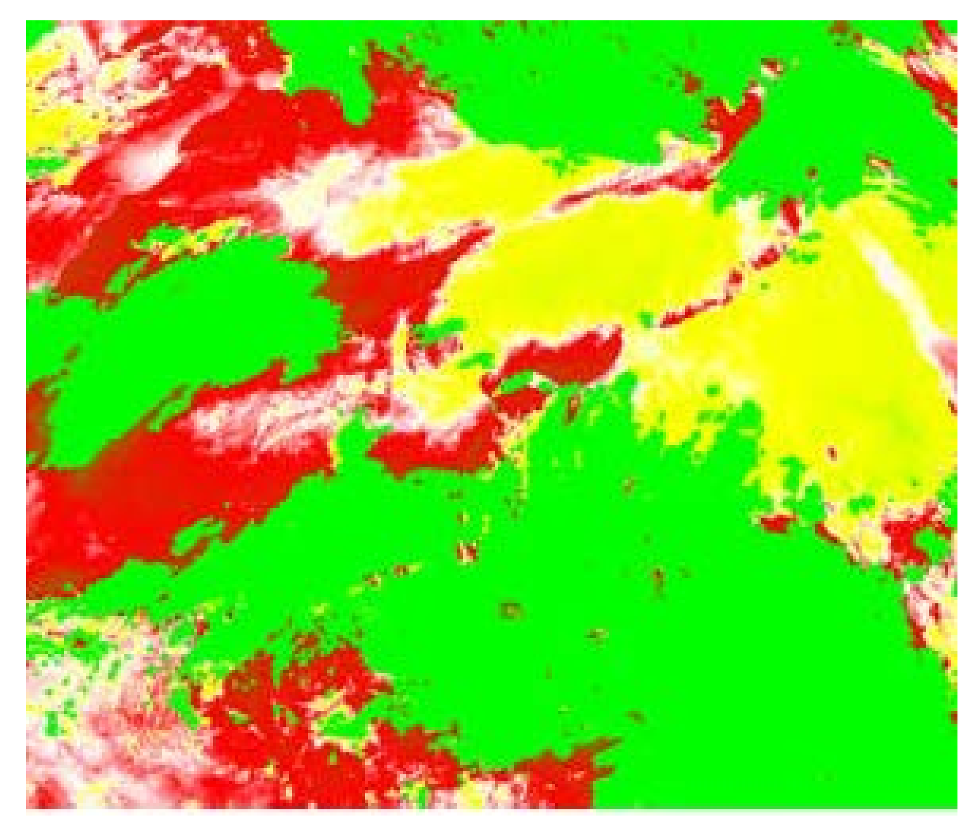

Figure 6. Difference between original image and pointwise average background.

- 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:

$$D^j_c = \frac{1}{T}\sum_{t=1}^{T} \frac{\sum_{i=1}^{n^j_t} |I^c_t(x_i,y_i) - B^c_t(x_i,y_i)|}{n^j_t}.$$

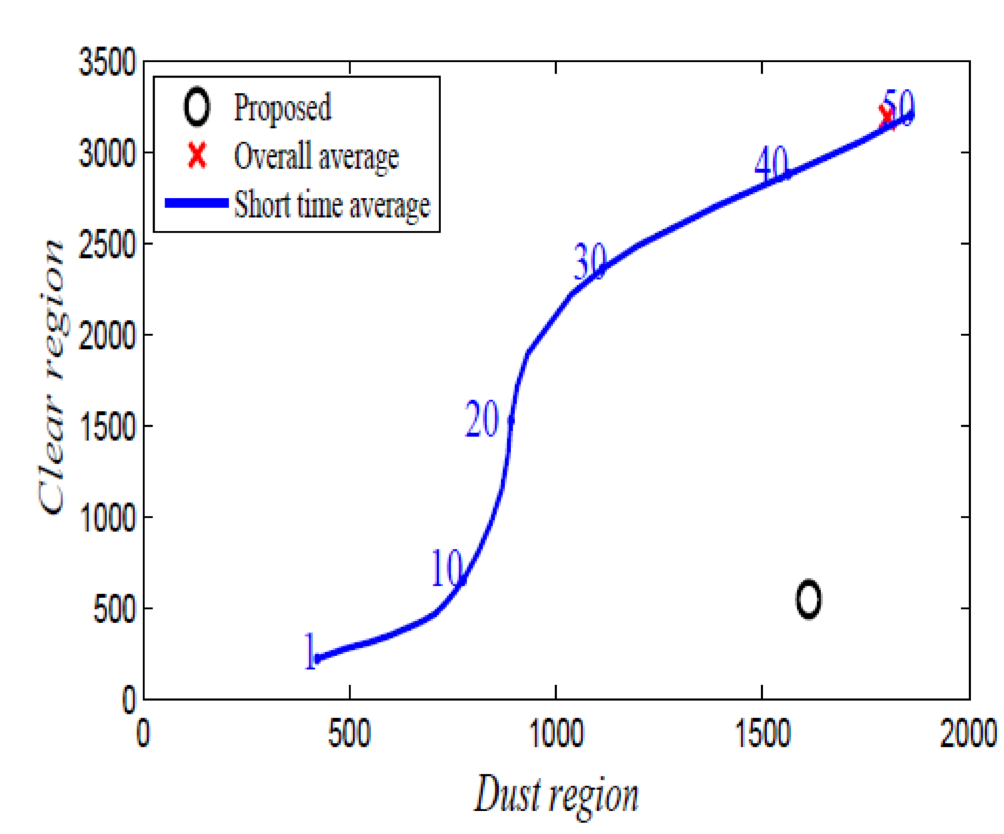

Figure 7. Mean absolute difference between original and background images.

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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