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COMBINING CALIPSO AND METEOSAT IMAGES TO STUDY THE DISTRIBUTION OF ATMOSPHERIC DUST

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ABSTRACT

The identification and tracking of atmospheric dust is important to many disciplines due to its impact on the climate and ecological systems. Sensors on-board existing imaging satellites such as MSG and CALIPSO provide good horizontal and vertical resolution, respectively, and therefore the resolution of any dust products derived solely from one sensor will be limited in the same manner as the sensor. We propose a new method of identifying dust distributions in the atmosphere using data from two separate satellite sources, the SEVIRI on-board MSG and the CALIPSO lidar. The approach employs a supervised classification method using texture data derived from a bank of Gabor filters. Once the dust has been identified, the SEVIRI data is augmented with vertical CALIPSO data to produce a 2½D dust cloud top height distribution.

Index Terms— Atmospheric dust, SEVIRI, CALIPSO, image texture analysis, remote sensing, Gabor filters

1. INTRODUCTION

Atmospheric dust particles have a wide ranging influence on climatic, atmospheric and ecological systems and impact on global warming, ocean circulation and the level hurricane activity. The ability of determine a fully three-dimensional (3D), spatio-temporal distribution of atmospheric dust would therefore be of great benefit to geoscientists working in a wide range of disciplines such as meteorology, climatology and oceanography. However, to do this there are many challenges that are still to be solved.

Major advances in the study of atmospheric dust particles have resulted from the use of networks of ground-based sensors and imaging satellites. The Spinning Enhanced Visible and Infra-Red Imagers (SEVIRI) on the ESA Meteosat Second Generation (MSG) satellites provide high-resolution, remotely-sensed images every 15 minutes. These can be used to provide 2D dust distributions, for example the EUMETSAT dust product [1], which have high horizontal resolution but little or no vertical information. In contrast, ground-based networks such as Aerosol Robotic Network (AERONET, http://aeronet.gsfc.nasa.gov/) [2] and EARLINET (European Aerosol Research LIdar NETwork) can measure the vertical structure of dust, but only over the location of individual measurement sites. Furthermore, as ground-based networks are confined to land they cannot monitor the two-thirds of the Earth's surface covered by oceans, greatly hindering their use in global-scale studies.

The CALIPSO satellite was launched in April 2006 and follows a 16-day repeating polar orbit [3]. Its on-board lidar produces continuous, along-track vertical sections of the atmosphere, thus providing information on the vertical structure of the lower atmosphere with a global coverage not previously available. In addition to the lidar, CALIPSO also has a 3 channel IIR sensor that measures the brightness temperature over a 64km cross-section centered on the overpass. Therefore, although the SEVIRI and CALIPSO data are complimentary and can, in theory, be combined to produce 3D dust distributions, their temporal and spatial resolutions are not well matched. SEVIRI images have good latitudinal, longitudinal and temporal resolution but very poor vertical resolution whilst CALIPSO's cross-section has excellent vertical and along-track resolutions but poor cross-track and temporal resolutions.

This paper addresses the key challenge of how to combine CALIPSO and SEVIRI data to study and quantify the distribution of atmospheric dust. Although our ultimate aim is to generate 3D time-varying distributions, here a methodology for determining an intermediate, static, 2½-dimensional (horizontal plus dust cloud top height) is presented. The proposed technique has three main stages. First, the CALIPSO overpass is registered to the SEVIRI images. This enables the CALIPSO vertical feature mask (VFM) to identify the location of any dust under the CALIPSO overpass in the SEVIRI image. The known dust locations within the SEVIRI image provide a training set which can be used in the second stage, which is the identification of dust locations elsewhere in the SEVIRI image. To do this a supervised classification algorithm is applied to textural derived from a Gabor filter bank.

The final stage is to use dust cloud top height information from the CALIPSO VFM to calibrate the conversion of SEVIRI radiance images to brightness temperature, thus augmenting the two-dimensional horizontal dust distribution with dust cloud top heights. These three stages are described in more detail below and are illustrated for the particular application of Saharan dust outbreaks.

2. IMAGE REGISTRATION

The first step of the image registration stage is to obtain a SEVIRI image that matches the time and geographical location of CALIPSO's overpass. SEVIRI images are generated at fixed time, whereas the VFM is tied to the CALIPSO grid pattern. Although the time varies with along track position, the approach adopted here is to assume that time is locally constant and to select the closest SEVIRI image to CALIPSO's overpass time. This is a reasonable assumption, as in the worst case the error with be ~7.5mins.

To simplify the registration, the SEVIRI images are first remapped so that the pixels are linear with latitude/longitude. The

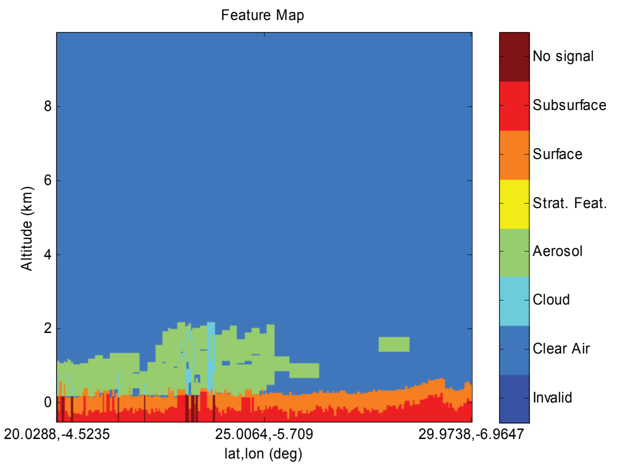


Fig. 1. Saharan dust outbreak on 21/02/2007. Reconstructed vertical feature mask from the CALIPSO data for an overpass of North Africa from UT 13:50.

geographical latitude and longitude of the VFM data entries enable them to be mapped to the corresponding pixel locations within the reprojected SEVIRI image. Figs. 1 and 2 show the CALIPSO VFM and the corresponding IR10.8 image for a Saharan dust outbreak from 21/02/2007.

2. DUST IDENTIFICATION

To identify dust in the SEVIRI image a supervised texture segmentation scheme is proposed. In this approach, the dust flag from the registered CALIPSO VFM is used to identify the locations in the overpass where dust is present, that are subsequently used as training data for a supervised segmentation algorithm. Each VFM entry is classified as one of 8 classes (see Fig.1) with the aerosol class being further divided into 8 sub-classes. The version of the algorithm used here is v2.01 [4] and in the VFM example shown in Fig.1, the aerosol feature entirely consists of the mineral dust sub-class.

Textural features were generated by applying a bank of 2D Gabor filters to the remapped SEVIRI image. The magnitude of the Gabor filters responses was selected as it has been shown to produce a consistently good segmentation performance and is simple to implement [5]. Gabor filters have also previously been used to identify other aerosols, namely black smoke caused by oil fires, in IR images and found to be more efficient and robust than methods based on features from the Gray Level Co-occurrence (GLCM) [6].

The Gabor filter parameters were set by selecting a fixed angular spacing for the filter orientation which defined the orientation bandwidth, B_θ. Normally, 4 or 6 orientations were selected to provide reasonable coverage in the spatial-frequency domain [5]. The radial bandwidth, B_r, was calculated to maximize the coverage in the frequency domain whilst minimizing filter overlap. The frequencies used were selected by calculating a peak frequency and then setting further values separated by 1 octave [7]. As lower values of frequency correspond to larger spatial variations, using too low a frequency produces responses that are spatially too large to be textural. Lower frequency values also require larger filters, which increases the computation time.

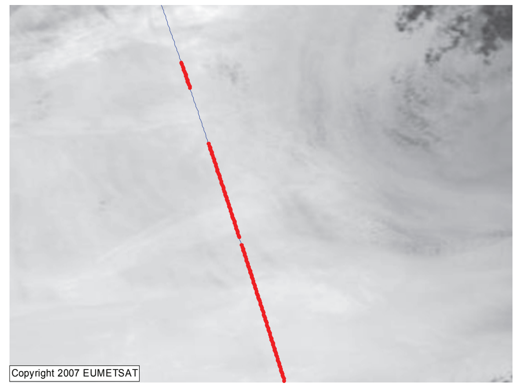


Fig. 2. IR10.8 MSG image from UT 13:45 on 21/02/2007 with the CALIPSO overpass marked in blue and dust locations in red.

Therefore, in our implementation only the 6 highest frequencies were considered. The extent of Gaussian envelope can then be calculated by setting the cut-off in frequency and angular direction to -6dB [5] and truncating the filter at $\pm 3\sigma$ [7].

The application of Gaussian smoothing is known to improve the performance of texture analysis using Gabor filters [8]. This can be achieved by applying a Gaussian filter whose size matches that of the Gaussian envelope of the corresponding Gabor filter to each of the Gabor filter bank responses.

The responses to the Gabor filter bank form a high dimension feature space. Issues of computational complexity make the direct application of an automated classification algorithm to this feature space impracticable. To make the process tractable, classification can be performed using a feature sub-set, ideally consisting of those filter responses that give a good discrimination between classes.

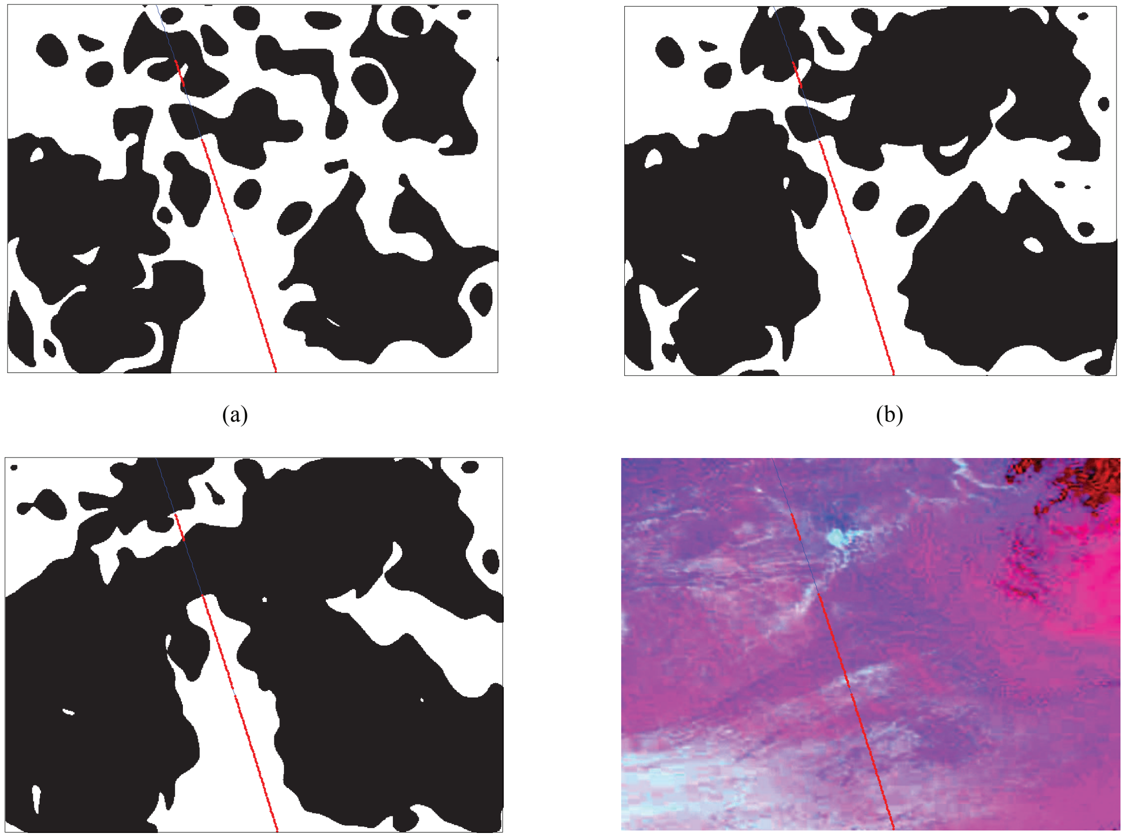
When there are two distinct textures to identify, the discrimination abilities of the Gabor filters can be ranked according to the overlap between the resulting PDFs for each class, allowing a suitable filter sub-set to be selected [9]. Although this may appear an attractive approach to segmenting the SEVIRI images into dust and non-dust categories, it is not appropriate as, in reality, the non-dust category can contain multiple textures such as clouds, other aerosols, and land and sea surfaces.

Instead, a sequential filter picking method is proposed, based on the vector selection algorithm of [10]. This is an iterative approach allows a feature vector to be built by adding one filter response at a time, using a quantitative measure of the classification performance achieved on the training set to select an additional filter at each step.

The Mahalanobis distance (MD) for each Gabor filter response is calculated using known dust pixels from the training set. Using the training data, an upper control limit (UCL) is defined using the Hotelling T-squared test, as the true covariance matrix is unknown [11]. The test treats the square MD values as T-squared values and classifies pixels as dust when the values are below the UCL. The overall classification performance is then evaluated for the training set using the geometric mean (GM) given by

$$GM = \sqrt{TP \cdot TN}$$

where TP and TN are the number of true positives and true negatives respectively [12].



(a) (b)

(c) (d)

Fig. 3. Detected dust (white) within the SEVIRI image of Fig. 2 with the CALIPSO overpass marked in blue and the dust locations marked in red. Results for a feature vector of length (a) 2, (b) 3, (c) 5 and (d) the corresponding MSG dust product image.

The filter with the best classification performance, i.e. the highest GM value, is selected. This process is then repeated using all other filters in conjunction with the filter already chosen and the filter that produces the greatest improvement in the *GM* is added to the feature vector. This process is repeated until the feature vector reaches the desired length. An alternatively approach is to keep adding filters to the feature vector until a particular level of classification performance is achieved.

The sequential filter selection approach mimics the optimal approach of evaluating every possible combination of filters for a given length feature vector but has a greatly reduced computational expense. It also provides a framework that allows texture measures derived from additional sources to the Gabor filter bank, for example the GLCM or morphological granulometries, to be incorporated, as can different metrics for evaluating the classification performance.

Fig. 3 shows the results from the classification process for the SEVIRI image of Fig. 2, using the sequential filter selection algorithm to create feature vectors of different sizes. The Gabor filter bank consisted of filters at 6 orientations (B_θ = 30˚) and at the 6 highest frequencies, giving a feature space consisting of 36 Gabor filter responses. Gaussian post filtering was applied using a Gaussian envelope 2/3 of the size of that used in the Gabor filter. Also shown is the MSG dust product for the same time and geographical location, in which the presence of dust is indicated by the colour magenta. It can be seen that the MSG dust product does not agree with the CALIPSO data for all locations on the overpass and therefore can not be regarded as ground truth. However, it does enable a qualitative visual comparison with the dust classification results to be performed.

Fig. 3(a) to (c) show that a more realistic classification performance is achieved as additional filters are added to feature vector. With a feature vector of length 5 some correspondence between the classification result and the perceived, observable dust in the MSG dust product is achieved. It is important to note that, as the training data is generated from the CALIPSO VFM, we expect the classification to be well-adapted to the CALIPSO overpass. The remaining area not under the CALIPSO overpass (the majority of the SEVIRI image) represents a new data set where no prior knowledge of the presence of dust exists.

3. DUST CLOUD TOP HEIGHT

Once the dust in the SEVIRI image has been classified the cloud top height can be found by first converting the SEVIRI radiance image to brightness temperature. Providing the dust is below 11km, the variation of temperature is linear with altitude. Robust regression using a bisquare function was used to determine the conversion between brightness temperature and altitude, calibrated using the CALIPSO data for dust under the overpass. This

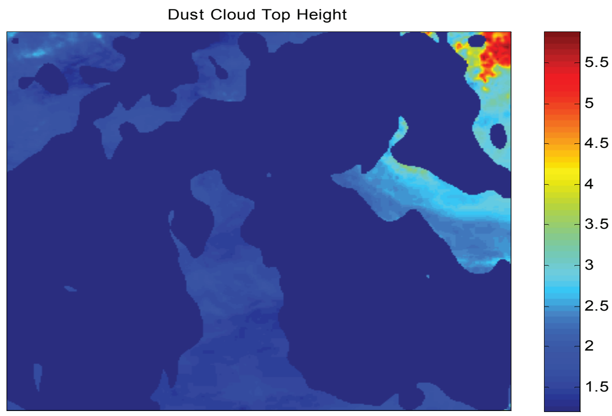


Fig. 4. Dust Cloud top height in metres derived using relationship between altitude from the CALIPSO overpass and brightness temperature from the SEVIRI image.

conversion was subsequently used to convert the brightness temperature to altitude for dust elsewhere in the SEVIRI image. Fig. 4 presents the results of this process for the dust classification result using a feature vector of length 5 from Fig. 3.

4. CONCLUSIONS AND DISCUSSION

A new approach to the identification of atmospheric dust has been presented. The method uses complimentary CALIPSO and SEVIRI data to produce a 2½D image of the dust cloud top height and is initially applied to an example Saharan dust outbreak. Our ultimate aim is to extend this approach to produce 3D, time varying images capable of underpinning the study of atmospheric dust distributions on a global scale.

Although, to date, a quantitative evaluation of the approach using data from other dust detection methods such as the IDDI or AERONET has not been performed, the work presented in this initial study shows the approach to be practical and to have much potential for further work. Validation against independent sources of dust data is the next phase of the work which will enable a quantitative performance evaluation.

A quantitative evaluation will also be used to further develop the sequential selection algorithm used for populating the feature vector. Issues to be investigated include alternative metrics and the incorporation of other texture features, either from other SEVIRI channels or derived using alternatives to Gabor filters. We also intend to use the quantitative evaluation methodology to compare the performance of the sequential feature selection approach with standard techniques for reducing the dimensions of multivariate data for classification purposes, such as principal component analysis.

Finally, the application of textural information from images matching the CALIPSO overpass will be applied to images of the same geographical region within a short temporal window. This would allow, for example, the texture of dust data from the IR10.8 SEVIRI image at UT 13:45 to be used to classify dust in the IR10.8 images at UT 13:30 and 14:00. Here, the assumption that the dust texture is constant over a short timescale would allow dust to be identified in SEVIRI imagery without a corresponding CALIPSO overpass, providing one happened sufficiently close in time.

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