A potential FeatureMask algorithm for the EarthCARE lidar

Gerd-Jan van Zadelhoff and Dave Donovan

Royal Netherlands Meteorological Institute, PO Box 201, NL-3730 AE, de Bilt, The Netherlands,zadelhof@knmi.nl

ABSTRACT

The Earth Clouds, Aerosol and Radiation Explorer (EarthCARE) is a combined ESA/JAXA mission to be flown in 2013. In this work, a potential FeatureMask algorithm for the EarthCARE high spectral resolution lidar is discussed which was developed within the ESA sponsored CASPER study. A feature mask identifies 'significant return' in the lidar signal. It does not specify the nature of the feature. In order to be able to derive reliable extinction and backscatter profiles, as well as a target classification, which specifies the nature of the feature (ice cloud, liquid cloud or aerosol layers etc.); an accurate feature mask is essential.

The algorithm relies on image reconstruction techniques and not on signal to noise ratios and thresholds only. The algorithm and results for a number of different scenes including ice clouds, liquid clouds and aerosol layers will be presented.

1. INTRODUCTION

The Earth Clouds, Aerosol and Radiation Explorer (EarthCARE) is a combined ESA/JAXA mission to be flown in 2013. EarthCARE will study the spatial (3D) distribution of clouds and aerosols and their impact on the Earth's radiative balance. To do this, the EarthCARE platform will carry a combination of active (a high spectral resolution lidar and Doppler radar) and passive sensors (Multi spectral imager (MSI) and Broad Band Radiometers (BBR).

In this work, a potential feature mask algorithm for the EarthCARE high spectral resolution lidar (ATLID) is discussed which was developed within the ESA sponsored CASPER study. A feature mask identifies 'significant return' in the lidar signal. It does not specify the nature of the feature. In order to be able to derive reliable extinction and backscatter profiles, as well as a target classification, which specifies the nature of the feature (ice cloud, liquid cloud or aerosol layer etc.); an accurate feature mask is essential. As the signal strength of aerosol or very optically thin ice clouds on the single shot grid can be comparable to the expected ATLID noise levels it was chosen to rely on image reconstruction techniques and not on signal to noise ratios and thresholds only. The main reason why an image reconstruction technique can be so effective for the EarthCARE lidar data is that in principle the ATLID Mie channel receives only particle backscatter, background noise and noise due to the Mie-Rayleigh cross-talk. It also ensures the derivation of a feature mask on the single shot resolution instead of directly going to a lower horizontal resolution of 1km. This enables both the use of variable masks, e.g. use only those profiles which are sure to have no clouds to derive the mean aerosol signals and calculation of feature fractions which can result in a better determination of higher order L2a and L2b products. The algorithm and results for a number of different scenes, both simulated and Calipso measurements, including ice clouds, liquid clouds and aerosol layers will be presented.

2. ALGORITHM DESCRIPTION

The lidar used by EarthCARE (ATLID) has a high-spectral-resolution type design. That is, the contribution to the return signal from the thermally broadened Rayleigh return and spectrally narrow elastic backscatter return (Mie) are separated. Thus, in principle, the extinction profile at the lidar wavelength along with the corresponding backscatter profile may be independently derived. Before this can be performed a feature mask needs to be created as an input to the extinction retrieval algorithm. The Mie signals are separated by a Fabry-Perot etalon. Due to this configuration, there is a large noise component in both the Mie and Rayleigh channels, dubbed as cross-talk. Cross-talk is Mie signal which ends up in the Rayleigh channel and vice versa. The cross-talk hampers more general methods purely based on signal to noise ratios. These are still possible for the ATLID signals but will only enable the masking of very high signals and therefore very optically thick ice clouds and water clouds. In most cases it will not be able to mask aerosol layers on a shot-by-shot basis.

Two methods are employed to retrieve the feature mask: the median-hybrid method [1] and the maximum entropy [2] method, both using the signal detection probabilities. Based on these two methods, coherent structures can be defined and features with a low signal to noise ratio can be distinguished from the noise only signals. Both routines implicitly use horizontal and vertical neighbor information to define structures. The choice for the use of the two methods is based on the specific benefits each of them have. The median-hybrid method is particularly good at finding coherent features while keeping edges constant (no smoothing effects beyond the features). The maximum entropy method adopted here convolves the data iteratively until a good balance is

© Proceedings of the 8th International Symposium on Tropospheric Profiling, ISBN 978-90-6960-233-2
Delft, The Netherlands, October 2009. Editors, A. Apituley, H.W.J. Russchenberg, W.A.A. Monna

found between smoothing of noisy features while still remaining a good comparison to the original data. Note that both methods assume that particle features are not single point events. Events of this nature would be missed by this algorithm. Future datasets should help to indicate if this would lead to a large set of missed events. In the following subsections the general description and use of the methods/calculations is given.

2.1. Median Hybrid Method

The hybrid median filter checks the entire image, pixel by pixel, using an n$*$n filter, where n is an odd integer of 5, 7 or 9. The center pixel is calculated using the two diagonals, the horizontal and vertical rows within this box. For each of the rows the median value is calculated, after which the median value of these four median values is taken. As this latter median is from an even number we take the third value of the sorted array (not the mean of two values in the center). The algorithm is very effective in removing single noise events and filling gaps. The median hybrid algorithm is run iteratively five times to ensure that the image has converged, e.g. there are no more changes in the image between this iteration and the next. As only median values are used, there are no smoothing edge effects. The only coherent structures which will not be detected this way are structures with a vertical or horizontal width of 1 or 2 pixels. Particularly horizontal stretched structures are at risk here as high optically thick water clouds (stratus or cumulus) may yield only 2 pixel thick clouds before the backscatter is completely reduced. To keep these important structures within the mask the hybrid median technique is used in a slightly altered version by using an n$*$3 box ensuring that also features of only two pixels thick, e.g. water clouds, are detected. The two masks are compared and only those additional features in the n$*$3 hybrid median results are added to the feature mask.

2.2. Maximum Entropy Method

With the main features found the next step is to find structures within the noisy part of the image. For this we use the original Mie signal probability data (P_{mie}) with all previously detected features set to 0. The method used to find the remaining features is a maximum entropy image restoration scheme[2]. The maximum entropy method selects that particular feasible image, from a large number of possible representations of the true image, which has the greatest entropy (E), taking into account the chi-square (χ^2) difference. This constrained maximum of E will be at an extreme of $E-\lambda\chi^2$ for a suitable Lagrange multiplier λ. The entropy of a probability distribution is a measure of the information content and can be defined as

$$E = -\sum[P_i log(P_i)], \quad (1)$$

With P_i ($>$0) the normalized probability in pixel i and $\sum P_i$=1. Next to the entropy there is also the (χ^2) for any retrieved image compared to the actual measured data, given by

$$\chi^2 = \sum \frac{(D_i - I_i)^2}{\sigma_i^2}. \quad (2)$$

This 'misfit' is represented by a single number depending on the original input probability data (D_i=P_{mie}[Hyb. Med Features=0]), the standard deviation in D_i (σ_i) and the probability data retrieved after a mathematical procedure to the data (I_i)

As the most obvious features are already detected and only a noisy image remains a very simple version of the MEM is used to check for more coherent features within the noise. In this case the different images are calculated by iteratively convolving the previous image with the following convolution kernel

$$\begin{pmatrix} 1 & 1 & 1 \\ 1 & 8 & 1 \\ 1 & 1 & 1 \end{pmatrix}$$

starting with the input data D_i. The kernel is normalized to ensure no signal loss when performing the convolution. For each of these images the E and χ^2 differences are calculated and compared to each other. When the optimum entropy probability image is retrieved, it is subsequently checked for its signal characteristics. From the optimal image the detection probability histogram is calculated. This histogram depicts the number of pixels within a probability bin. The histogram consists of two major parts, a Gaussian like peak representing the noise and an excess to the Gaussian signal due to coherent features.

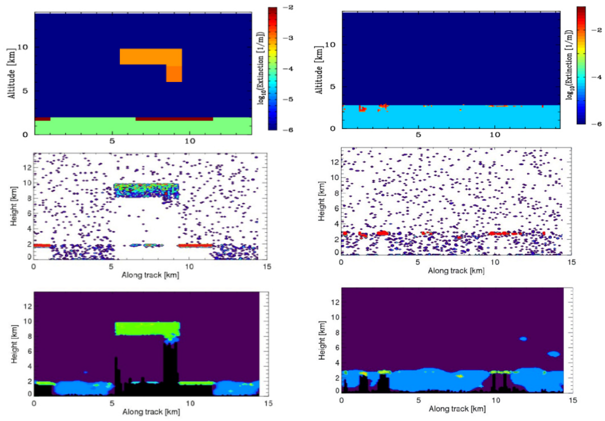

Figure 1. Two ECSIM examples. Left column shows a test scene with an ice cloud, liquid cloud and aerosol layer. The right column a LES simulated cumulus case with aerosol layer. For each example. Top: Slice of the extinction through the ECSIM scene. Center: ATLID simulated Mie channel signals. Bottom: Retrieved feature mask.

3. RESULTS

The algorithm results are presented using two types of scenes. First, results from the EarthCARE simulator and second using Calipso measurements. The Calipso instrument has both signals at 532 and 1064nm. As this algorithm was designed to work for the Mie channel of an HSRL lidar it expects no coherent background signals, especially non-uniform. As the molecular backscatter in the 532nm channel is evidently present and has a strong height/pressure dependence, the signal is in principle not suited for this algorithm. In the 1064nm channel the molecular signal is negligible and it is therefore the best possible signal from a satellite for testing the algorithm. The only drawback of this choice is that aerosol signals will also be smaller in this channel, which will result in a non-detection of layers as is visible in one of the examples.

3.1. EarthCARE simulator examples

The algorithm was developed using scenes and results from the EarthCARE simulator, to best mimic the to be expected ATLID signals and noise levels. The first test case is presented in Figure 1 (left column). The scene itself consists of three particle regions. An ice cloud, with an optically thin and optically thick part, a water cloud and an aerosol layer up to 2 km. The results are presented in three plots: First the extinction slice through the scene as was created in the EarthCARE simulator (the model truth); Second the detection probability between 0 (white) and 100 % (red) for the Mie channel and third the feature mask as was derived from the signals (black; no signal, purple; molecular; blue colors are derived using the max-entropy method, green & orange colors come from the hybrid median method). The second ECSIM case (Figure 1; right column) is based on a LES study by H. Barker, using the same color schemes. In this case cumulus clouds are present with cloud top roughly at 2.5 km and an aerosol layer throughout the entire scene with the same maximum altitude. The very optically thick clouds are not completely penetrated by the lidar, visible by the small vertical extent in the synthetic ATLID signals and the lack of signals below some of the clouds. The clouds themselves are well defined in the feature mask by the hybrid-median method. The aerosol layer is detected using the maximum entropy method for the entire regime. There are two small mis-identifications above 2.5 km height beyond 11 km along track. A more thorough look at the precise Gaussian fit to the histogram data may result in a better fit of the features for this particular case. Both examples in Figure 1 show that the to be expected measurements from ATLID will be noisy but, with an algorithm as described here, all features can be identified as long as the signals are not completely extincted.

3.2. Calipso 1064nm examples

As the algorithm is intended to look at lidar data from space it is appropriate to test it with available lidar data from space. As discussed above, the 1064nm CALIOP channel is the best data stream to check the algorithm , due to its lack of molecular backscatter. The vertical resolution of the CALIOP data changes at two points at ≈8 and ≈19 km. The current version of the algorithm works only using single vertical and horizontal resolutions throughput the scene. This was deliberately chosen as a change in resolution will alter the noise behavior from one to the other regime. In all the scenes shown below each of the vertical resolution regimes has been treated separately. This means that there has been no contact between the signals above and below the resolution change. As the Calipso data is different from the ECSIM ATLID data the maximum entropy convergence criterium was not been enabled for these examples, instead the maximum entropy mask is retrieved using the 20th convolved iteration.

In the first Calipso scene (Figure 2) one can clearly distinguish an ice cloud and different aerosol layers with a lot of noise in the latter regime. Most of the ice cloud resides in the second vertical resolution regime with only the lower parts extending into the lowest regime.

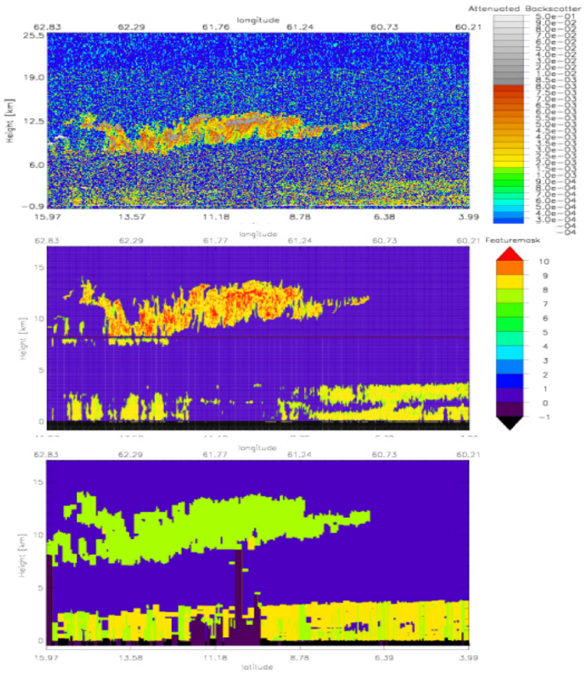

Figure 2. Comparison of the two masks for an ice cloud and aerosol scene. Top panel: Part of the measured 1064nm backscatter signal. Center panel: corresponding atlid-featuremask and bottom panel: VFM-target classification

Note that the vertical axis of the raw data image goes up to 25 km while both feature masks go up to 17 km. The atlid-featuremask has values between -2 and 10, where -2 is subsurface (black), -1 no data (purple; not indicated here), 0 most likely molecular (blue) and 10 most likely particles (red). Shown are the retrieved features with values 6 to 10 indicating that the backscatter originated likely to most likely from particles. A horizontal line indicates the height at which the resolution changes. The VFM mask[3] (clouds:green, orange:stratospheric features, aerosols:yellow, molecular:blue, no data:purple and surface:black) and atlid-featuremask show very similar results at first glance but when looking in detail show some significant differences.

The ice cloud in the upper regime was found directly with the median hybrid routine, visible by both the large mask values and the sharpness of the edges (no visible smoothing compared to the VFM mask). The lower part of the ice cloud is also detected in the lower regime. The aerosol detections in the lower left part is more patchy compared to the VFM mask, but seems justifiable when looking at the 1064nm raw data. On the right part the atlid-featuremask clearly distinguishes the two layers as is seen in the data. The VFM mask fills in nearly the entire area. This is most likely due to the way the VFM masks is created by the smoothing needs to distinguish the different targets. One of the main differences between the two masks is that the VFM mask is based mostly on the 532nm data and the atlid-featurmask on the 1064nm data. The goal of the atlid-featuremask is to identify at which points the backscatter signal is due to particles and which is due to noise and therefore molecular, it actually wants to make the distinction on an as high as possible resolution. The VFM mask is one step further down the retrieval chain in the sense that it is a target classification mask, e.g. separating clouds and aerosols from each other. It therefore needs to smooth more of the data to retrieve reliable signals to distinguish between the different target types.

A final example is given of a scene where the two masks show very different results (Figure 3). The atlid-featuremask and VFM mask show very different results above roughly 8 km, with the latter showing extended features not retrieved by the atlid-featuremask. Below 8 km the features look very similar with a number of liquid and mixed phase clouds. Again the atlid-featuremask shows sharper transitions mostly due to the use of the median-hybrid method compared to a smoothing method as is used for retrieving the VFM mask. The non detection of the upper layer is caused by an elevated aerosol layer which is nearly completely missed by at 1064nm (left upper panel) while it is obviously there in the 532nm channel (lower left panel) and would have been easily detectable if a similar signal had been available in 1064nm signals. There is a hint of the lowest of the two layers (between 8 and 11km) in the 1064nm channel and when checking the atlid-featuremask in more detail the layer was retrieved as 4 and 5, indicting between likely molecular and unknown, but so are a large number of other pixels. If anything, the comparison shows the benefit of going to lower wavelength. Similar layers will immediately show up with the ATLID 355nm Mie signals.

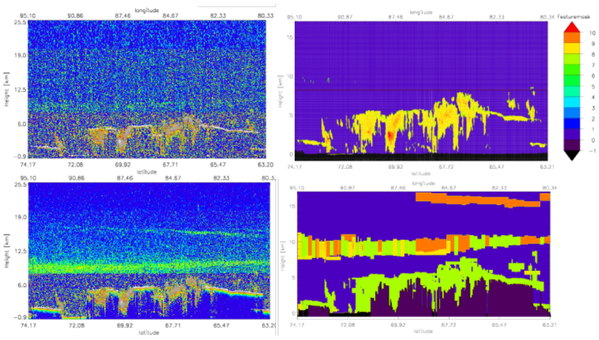

Figure 3. Comparison of the two masks for a cloud and aerosol scene Top left panel: Measured 1064nm backscatter signals. Top right panel: corresponding atlid-featuremask, bottom left panel: 532nm signal of the same area and bottom right the VFM-target classification. Note the two elevated layers seen at 532nm and not at 1064nm, giving rise to the main differences in the two masks

4. CONCLUSIONS

A new FeatureMask algorithm for the ATLID lidar signals has been constructed adopting image reconstruction techniques. The use of these techniques are based on the HSRL configuration of the ATLID lidar, which separates the Mie and Rayleigh signals. This leads to a Mie channel with only particle backscatter and additional noise. Both the mask and signals can be downscaled to lower resolutions when a higher signal to noise is needed. The high resolution atlid-featuremask can both be used to choose which signals should be combined and can be used as a feature fraction to combine only relevant profiles. The lower resolution mask and feature fraction can be used for all higher order products which need the backscatter signals.

The algorithm has been tested using both EarthCARE simulator data, for which it was originally built and the 1064nm Calipso data which resulted in a very good comparison with the standard VFM target classification and eye-fitting of the raw data. The algorithm will be worked on in the coming ESA sponsored ATLAS project, where it will be further refined and optimized. Future tests should include ground based and/or aircraft HSRL data and ADM data (when available).

ACKNOWLEDGMENTS

The Calipso data were obtained from the NASA Langley Research Center Atmospheric Science Data Center.

REFERENCES

Russ, J., 2007: The Image Processing Handbook, 5th Ed.CRC Press, 214-224 pp.

Skilling, J. and S. Gull, 1985: Algorithms and Applications. D. Reidel Publishing Company, 82-132 pp.

Vaughan, M., K. Powell, and D. Winker, 2005: CALIOP ATBD Part 2: Feature Detection and Layer Properties Algorithms. Tech. rep., SAIC. Available from http://www-calipso.larc.nasa.gov/resources/project_documentation.php.