A New Method for Determining Cloud Transmittance and Optical Depth Using the ARM Micropulsed Lidar

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ABSTRACT

Cirrus clouds play an important role in the climate through their optical and microphysical properties. The problem with measuring the optical properties of these clouds can be partially addressed by using lidar systems. The calibration of backscatter lidar systems, in particular, typically relies on the known molecular (Rayleigh) backscatter, which is a function of temperature, pressure, and chemical composition of the air. This paper presents an improved method for determining the cloud transmittance, and thus optical depth, derived from backscatter lidar measurements. A system of equations is developed in terms of a proposed metric that is required to possess a minima, and has a unique solution for the gain, offset, and transmittance. The new method is tested on a synthetic case as well as using data from two different lidar systems that operate at two different wavelengths. The method is applied to lidar data collected by the lidar operating at the central Pacific island of Nauru under the auspices of the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) Program.

1. Introduction

It is well known that cirrus clouds play an important role in the global climate due to their high frequency of occurrence and high altitude (Mace et al. 1998; Stephens et al. 1990). In an ongoing effort to assess the effects of cirrus clouds on the climate, many field experiments have been performed to understand the radiative and microphysical properties of these clouds. Among the various instruments used in these experiments, lidars emerged as simple and powerful probes in the investigation of the optical and microphysical properties of clouds.

One key optical property measurable by lidars is the transmission of the laser through cirrus clouds, from which the optical depth of cirrus is determined. Although this method for determining optical depth of cirrus is limited to optically thin clouds, data obtained from this measurement approach has several advantages over optical depth information extracted from reflected solar radiances or emitted IR radiances (Miller et al. 2000). A principal advantage of this method is the radiatively weaker dependence of scattering phase function on the retrieval, and optical depth, leading to more accurate retrievals.

This paper describes a new algorithm developed to analyze lidar data. The algorithm differs from previous similar algorithms in that backscatter data from both sides of the cloud are used to arrive at a consistent estimate of three parameters (gain, offset, and transmittance). The solution of this nonlinear system for the three parameters is less susceptible to noise and resolves the ambiguity in the offset value not achieved by previous methods.

In section 2 the paper briefly introduces the previous lidar transmission approach. Section 3 describes the new algorithm and an application on a synthetic case to illustrate the advantages over other approaches. Results of the algorithm applied to data collected at the Atmospheric Radiation Measurement (ARM) Program Southern Great Plains (SGP) site from two different lidar systems are presented in section 4. A summary of results and conclusions are provided in the final section.

2. Lidar transmission method

Young (1995) used the backscatter signal measured by a ground-based lidar together with the known atmospheric backscatter to devise a simple two-independent-window method for determining the transmittance of a cloud. Following his reason, the measured lidar-signal voltage in a region below the cloud can be expressed as
y(r) = \frac{m}{r^2} \beta_m(r) T_m^0(0, r) + n, \quad (1)

while in a region above the cloud the relationship becomes

y(r) = \frac{m}{r^2} \beta_m(r) T_m^0(0, r) T^2 + n. \quad (2)

Here \( m \) is a system constant, \( \beta_m(r) \) is the molecular backscatter coefficient at range \( r \), \( T_m \) and \( T \) are the molecular and the cloud transmittances, respectively, and \( n \) is the offset. The assumption made here is that aerosol is absent in these two regions. Included in the system constant are the gain of the lidar, the overlap function, and receiver area, etc., while the offset accounts for the background light, detector dark current, and amplifier and digitizer offset voltage. Molecular backscatter is calculated as a function of pressure and temperature, which are determined from the soundings.

With the modeled signal introduced as

\[ x(r) = \frac{1}{r^2} \beta_m(r) T_m^0(0, r), \quad (3) \]

our system of equations becomes

\[ y_1 = mx_1 + n \quad y_2 = mx_2 T^2 + n, \quad (4) \]

where we introduce subscripts to denote the regions below the cloud (1) and above the cloud (2), respectively. At this point, a linear regression (Taylor 1982) of the measured signal \( y \) against the modeled one \( x \) can be performed for each of the two regions to yield the offset \( n \) and the calibration factor \( m \) for the low-region case or the product \( mT^2 \) for the high-region case, respectively. The system (4) separates into two independent systems with two equations and two unknowns:

\[ \langle y x \rangle_1 - m \langle x^2 \rangle_1 - n \langle x \rangle_1 = 0 \]

\[ \langle y \rangle_1 - m \langle x \rangle_1 - n = 0 \quad (5) \]

\[ \langle y x \rangle_2 - mT^2 \langle x^2 \rangle_2 - n \langle x \rangle_2 = 0 \]

\[ \langle y \rangle_2 - mT^2 \langle x \rangle_2 - n = 0, \quad (6) \]

where overbars indicate an average quantity, and subscripts are associated with a low region (1) or high region (2), respectively. The two systems of equations in (5) and (6) are solved independently:

\[ m = \frac{\langle y x \rangle_1 - \langle y \rangle_1 \langle x \rangle_1}{\langle x^2 \rangle_1 - \langle x \rangle_1^2} \]

\[ n = \frac{\langle y \rangle_1 \langle x^2 \rangle_1 - \langle y x \rangle_1 \langle x \rangle_1}{\langle x^2 \rangle_1 - \langle x \rangle_1^2} \quad (7) \]

\[ mT^2 = \frac{\langle y x \rangle_2 - \langle y \rangle_2 \langle x \rangle_2}{\langle x^2 \rangle_2 - \langle x \rangle_2^2} \]

\[ n = \frac{\langle y \rangle_2 \langle x^2 \rangle_2 - \langle y x \rangle_2 \langle x \rangle_2}{\langle x^2 \rangle_2 - \langle x \rangle_2^2}. \quad (8) \]

From the ratio of the two calibration factors, the square of the transmittance can be determined. Two values of offset are determined from this system of equations and there is no reason to expect these values to be the same. This is a problem, as the offset is essential in determining the cloud backscatter and transmittance from the lidar equation and, thus, in establishing the level of confidence in determining the two calibration factors by using two independent linear fits derived arbitrarily from a coupled system of equations (4). In the next section, we address this problem by developing a new method for computing the calibration factor, the offset, and the transmittance from one system of equations that produces a unique solution for the above parameters.

3. A new lidar transmission algorithm

To solve the problem of fitting the measured lidar signal to a model for both regions, we introduce the metric

\[ \delta^2 = \sum_{i=1}^{k_1} W_{i,1} (y_{i,1} - mx_{i,1} - n)^2 \]

\[ + \sum_{i=1}^{k_2} W_{i,2} (y_{i,2} - mT^2 x_{i,2} - n)^2, \quad (9) \]

where the first sum is performed for the region below the cloud and the second sum is performed for the region above the cloud; \( k_1 \) and \( k_2 \), respectively, are the number of points for each of these regions, and \( W_i \)'s are simply weighting coefficients that take into account the effect of noise, having their sum normalized. The procedure for determining the weighting coefficients as well as the cloud boundaries is presented in the appendix.

We now find the parameters \((m, n, T^2)\) that minimize the above expression, by imposing that the partial derivative of \( \delta^2 \) with respect to each of the parameters is zero. This results in the following system of equations:

\[ \langle y x \rangle_1 - m \langle x^2 \rangle_1 - n \langle x \rangle_1 = 0 \]

\[ \langle y \rangle_1 - m \langle x \rangle_1 - n = 0 \]

\[ \langle y x \rangle_2 - mT^2 \langle x^2 \rangle_2 - n \langle x \rangle_2 = 0 \]

\[ \langle y \rangle_2 - mT^2 \langle x \rangle_2 - n = 0, \quad (10) \]

where we use the notation

\[ \langle y x \rangle_{(1,2)} = \sum_{i=1}^{k_{i,2}} W_{i(1,2),1} x_{i(1,2),1}, y_{i(1,2),1}, \quad (11) \]

The above system of equations is a nonlinear system of three equations and three unknowns, in contrast to (5) and (6), which are usually solved for determining the same unknowns. It is observed here that the first two equations in (10) appear identical to the first equations in (5) and (6), while the last equation in (10) is a weighted sum of the last equations in (5) and (6).
Fig. 1. Synthetic case: (a) relative error for the simulated signal; (b), (c), (d) relative errors in transmittance, gain, and offset for the new method (dots) and old method (solid line). The computed variances, as explained in text for the new method, are shaded.
Conclusion is that our system of equations reduces to the conventional one for particular choices of the weighting coefficients. It is also clear that, since the requirement for a minimum in the proposed metric is more general than in two separate ones (which is the case with the old method), the new method will be the appropriate one for solving the problem for lidar calibration.

The unique solution for (10) is

$$
T^2 = \frac{(\langle x \rangle_1 \langle x \rangle_2 \langle xy \rangle_1) + \left[(\langle x^2 \rangle_2 - \langle x \rangle_1^2)(\langle y \rangle_1 + \langle y \rangle_2)\right] + \left[(\langle y^2 \rangle_2 - \langle y \rangle_1^2)(\langle x \rangle_1 + \langle x \rangle_2)\right]}{(\langle x^2 \rangle_1 - \langle x \rangle_1^2) - m^2(\langle x^2 \rangle_1)}
$$

and

$$
m = \frac{(\langle xy \rangle_1 - [(\langle y \rangle_1 + \langle y \rangle_2)]\langle x \rangle_1)}{(\langle x^2 \rangle_1 - \langle x \rangle_1^2) - T^2(\langle x \rangle_1)}
$$

The unique solution for (10) is

$$
n = \frac{(\langle xy \rangle_1 - m(\langle x^2 \rangle_1))}{(\langle x \rangle_1)}.
$$

Starting with the definition of the variance of a variable that can be expressed as a function of two independent variables $F(x, y)$,

$$
\sigma_F^2 = \sqrt{\left(\frac{\partial F}{\partial x}\right)^2\sigma_x^2 + \left(\frac{\partial F}{\partial y}\right)^2\sigma_y^2},
$$

and applying it to our variables described in (12), we can deduce the following expressions:

$$
\sigma_F^2 = \sqrt{\sum_{i=1}^{n_1} \left(\frac{\partial F}{\partial x_i}\right)^2 \sigma_x^2 + \sum_{i=1}^{n_2} \left(\frac{\partial F}{\partial y_i}\right)^2 \sigma_y^2},
$$

where $F$ can be any of our retrieved variables. We also assumed that the variance in signal ($\sigma_x$) is the same for both regions and we neglected the variance in the modeled signal ($\sigma_x = 0$), because errors in the molecular profile model will usually be much smaller than the lidar measurement errors.

The above procedure was tested for a synthetic case. The modeled signal was computed for two fixed windows as Rayleigh backscatter for a real profile of temperature and pressure, and then corrected to account for molecular absorption and range. The synthetic signal was derived as follows: 1) gain and offset were applied to the modeled signal; 2) for the upper window, a correction was applied to simulate the decrease in the signal due to transmittance through a cloud; and 3) zero mean Gaussian white noise was applied to the resulting signal. The standard deviation level of noise was randomly varied for each synthetic lidar profile. In total, 1440 lidar profiles (equivalent of one per minute out of 24 h) were simulated, and the resulting values for gain, offset, and transmission were determined. For comparison purposes, the old method (i.e., Young’s method) was applied to yield values for the same parameters. The results from a simulated case in which the lower window was set between 5500 and 9000 m, and the upper window between 11 000 and 16 500 m, respectively, while the values used for a gain, offset, and transmittance were set to be 100, 10, and 0.35, respectively, are shown in Fig. 1. From the figure we see that the new proposed method is significantly more accurate than the old one, yielding reasonable values for all three parameters, with greatest accuracy for the gain (errors are less than 5%, and the calculated values deviate from the actual values by less than 2%) and poorer accuracy for the transmittance (errors are large, with calculated values within 20% from the expected values). It is noted that there is a tendency for the old method to underestimate the gain and offset and overestimate the transmittance. For the new method, the transmittance is somewhat overestimated, but otherwise the gain and offset are undisturbed. In the case when the window intervals are reduced to 1500 m each (not shown here), the errors increase as one would expect, but the new method still gives reasonable results, while the old one yields parameter values that fail to give any physical values for transmittance, demonstrating the improvements made possible by the new method. Averaging several pro-

![Fig. 2. MPL backscatter signal (solid line) and modeled signal (dashed line), in arbitrary units as a function of altitude, cloud boundaries from proposed algorithm (dotted lines), and calculated transmittance (T).](image-url)
files and/or smoothing the signal is not necessary; thus, errors associated with such procedures are eliminated (Ansmann et al. 1992). Nevertheless, given the level of noise present in such an instrument, errors remain an issue, but, based on tests done for synthetic cases, the values obtained for gain and offset can be considered reliable. These parameters are subsequently used for computing vertical profiles of the cloud backscatter coefficients, which are essential in inverting the lidar equation.
Fig. 4. RL: (a) calibrated attenuated backscatter, (b) transmittance, (c) gain, and (d) offset as functions of time. The shading in (a) represents cloud backscatter (scale with units given in top right); the percentage next to the units is for profiles successfully processed. The shading in (b),(d) represents variance associated with each variable.
4. Application to experimental data

To illustrate an application of the new method, we processed lidar profiles obtained from two lidars that are operational at the ARM SGP site. The Raman lidar (RL) operates at 355 nm and has 39-m vertical resolution, while the micropulse lidar (MPL) operates at 523.5 nm and has 90-m vertical resolution. Both lidars have a temporal resolution of 1 min. Descriptions of both RL and MPL systems characteristics as well as signal preprocessing are available on the ARM Web site (http://www.arm.gov/).

In Fig. 2, the backscatter signal (which was corrected for background, afterpulse, and overlap in the preprocessing stage) measured by the MPL as a function of height (solid line) along with the modeled signal fit (dashed line) for a particular time are plotted. Cloud boundaries as determined by the proposed algorithm are also represented (dotted lines) along with calculated transmittance for this profile ($T = 0.57$). The relatively strong returns between roughly 6 and 8 km are due to a quasi-stable cirrus cloud.

In Figs. 3 and 4, the retrieved variables are plotted as functions of time for the two instruments. The errors associated with each variable lie within the shaded region. We can see that the transmittance shows a relatively smooth behavior with respect to time. However, the gain exhibits some fluctuations around a mean value, which was reported before for these instruments. We also see that during daytime (roughly 0000–0100 and 1300–2400 UTC), due to solar radiation, the level of noise increases and, as expected, the errors for all variables increase. Related directly to the measured signal, the offset shows the largest variations. This feature, however, can be exploited to our advantage by filtering out profiles that display large variations for offset, gain, or transmittance as typically occur in the daytime. For these figures we chose to represent all profiles for which the computed transmittances were less than 1.2. The numbers in the top right corner represent the percentage of profiles that were successfully processed. Since the calibration procedure is based on measured data, the transmittance is influenced by the possible multiple scattering (MS) events. However, for optically thin clouds, the MS effects are negligible.

In order to further test our new method, we compared the transmittances deduced from these two different lidars. In Fig. 5, the scatterplot of transmittance shows a good correlation between these two instruments, especially during nighttime (Fig. 5a) when solar radiation does not alter the received signal. The fitting slopes for the transmittance cases are 0.94 during nighttime and 0.79 during daytime. Differences in results obtained from the two lidars can also be due to the fact that the two lidars are not collocated and to differences in specifications.

Because the present method is intended to be used as an operational method for processing the ARM lidar data, two days of data have been processed, as shown in Fig. 6. The data was collected by the ARM’s MPL system located at Nauru (0.521°S, 166.916°E). We can see that the cloud boundaries are well determined, the values for transmittance show a relatively smooth variation with time, and the noise is filtered out.

5. Summary and conclusions

Lidars are instruments that are generally sensitive enough to detect even the thinnest cirrus layers that lie close to the tropopause. Measurements obtained from lidar systems have been used to study cirrus, providing information about their geometry and even some information on their optical properties. The latter requires that the return signal measured by the instruments usually be calibrated using known molecular (Rayleigh) backscatter. This is a function of temperature, pressure, and chemical composition of the air.

Assuming that there is no aerosol present in a region below and above the detected cloud, a simple linear fit between predicted Rayleigh scatter and measured backscatter can calibrate the measured signal. In the past, two separate fits were performed for each region (low and high), from which the gain and offset of the instrument were deduced. Further, from the ratio of the two gains, the square of the transmittance of the cloud could be calculated. The retrieval of two values for the offset, however, is problematic. A solution to this problem, for the ground-based lidars, was to determine the
Fig. 6. Time dependence of the MPL backscatter coefficient and transmittance for two days at Nauru: (a) backscatter and (b) transmittance for 17 May 1999; (c) backscatter and (d) transmittance for 21 May 1999. Shadings as in Figs. 4 and 5.
offset from the signal returns at higher altitudes (30 km or more). However, in the case of airborne lidars looking down, this approach cannot be used. In the new approach presented here, the problem is solved by making a single fit for both windows at a time, which produces a single offset, thus removing the calibration ambiguity. The system of equations that follows from our requirement that the proposed metric has a minima is solved for the three parameters that enter: gain, transmittance, and a single offset.

Experimental data obtained at the ARM site at SGP were used to evaluate the performance of this new method. In contrast to the previous techniques, the solution obtained here is more robust to the level of noise present in the signal. It is noted here that for both gain and transmittance, in many cases, the two schemes yield similar results, but that the old method tends to overestimate the latter. It is clear now that the new method, by the fact that it has a unique solution, resolves the ambiguity of the offset value that the old method introduced. The method of solution presented here allows for the estimation of the errors in the retrieved parameters whose sources lie in the measured signal and in the modeled signal. The technique has been found to be useful as a filter to discriminate against poor signals.

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APPENDIX

Determining the Weighting Coefficients

The values for the weighting coefficients as well as the cloud boundaries are determined using the following algorithm.

1) From preset lower and upper windows, using equal values for the weighting coefficients, determine the gain, offset, and transmittance.

2) Using the above determined values, recompute the weighting coefficients as the inverse of the distance between the measured signal and the one being modeled.

3) Using the above values for weighting coefficients, recompute the values for gain, offset, and transmittance.

4) Define a threshold value for cloud-detection purpose; find the maxima for the difference between signal and fit; test if it is greater than the threshold; from this level go up and down until the difference becomes less than threshold; repeat the procedure to find other cloud layers; determine the cloud top and bottom.

5) Using the cloud boundaries, redefine lower and upper windows; the sizes of the windows are set to 2500 m for the lower window and 5500 m for the upper window, respectively.

6) Repeat steps 1 and 2 using these new windows to determine gain, offset, and transmittance.

7) Repeat steps 1–6 for each individual profile; reject it if transmittance is greater than unity or less than zero, or if gain is negative.

8) As an option, a filtering scheme is used: for each profile the weighting function is recomputed using a weighted sum of the averaged values for gain and offset and the computed values for the same variables; these new weighting coefficients are used to compute new values for gain, offset, and transmittance. Use of this filtering procedure helps in reducing the level of noise in the transmittance as well as in gain and offset.

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