NOAA GOES-R AWG Cloud Height Algorithm (ACHA)

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Abstract

The AWG Cloud Height Algorithm (ACHA) generates cloud height and associated products from multiple long-wave infrared channels on geostationary and polar orbiting satellite imagers. While initially designed only for the GOES-R Advanced Baseline Imager (ABI), it has been extended to handle the infrared channel sets from most current imagers. This paper describes ACHA and some of the modifications made to improve its performance for the Atmospheric Motion Vector (AMV) applications.

ACHA INTRODUCTION

The AWG Cloud Height Algorithm (ACHA) was originally developed to serve as the cloud height algorithm in the software suite developed by the GOES-R Algorithm Working Group (AWG) for the Advanced Baseline Imager (ABI). The ABI version of ACHA operated on the 11, 12 and 13.3 µm channels. ACHA has since been modified to handle the 6.7 and 8.5 µm channels and can therefore process data from many current geostationary and polar orbiting imagers to be described later. ACHA uses analytical radiative transfer equations in an Optimal Estimate (OE) framework. The fundamental ACHA products are the cloud-top temperature, cloud 11 µm emissivity and a microphysical index (β). NWP profiles are used to convert cloud-top temperature to height and pressure. Infrared scattering models are used to convert emissivity and β into optical depth and particle size. Lastly, ACHA estimates the true cloud top and cloud base heights. A pressure altitude expressed in kilo-feet is also generated for aviation applications. ACHA generates uncertainties for the temperature, height, emissivity and β products based the OE diagnostics.

MATHEMATICAL DESCRIPTION

This section describes the ACHA algorithm. Heidinger and Pavolonis (2009) describe the two-channel version of ACHA which uses the 11 and 12 µm channels. The equations given in that paper are still valid. In the following discussion, only those equations that are needed for the three-channel ACHA are given.

The basic radiative transfer equation employed in ACHA is shown below in Eq (1). In this equation, $T_c$ is the cloud temperature, $e_c$ is the cloud emissivity, $R_{obs}$ is the observed radiance, $R_{clr}$ is the clear-sky radiance, $R_{ac}$ is the radiance emitted above the cloud, $t_{ac}$ is transmission above the cloud and $B$ is the Planck function. All terms in (1) are for a given channel.

$$R_{obs} = e_c R_{ac} + t_{ac} e_c B(T_c) + R_{clr}(1 - e_c) \quad (1)$$

The microphysical information comes from the β parameter (Parol, 1995), which can be derived from the ratio of optical depths or from emissivities for a spectral pair of channels 1 and 2 shown in Eq (2). β is similar to the Angstrom exponent used in aerosol remote sensing. β allows the relationship of a channel X's emissivity to be related to the 11 µm cloud emissivity as follows.

$$e_c(X \ m) = 1 - [1 - e_c(11 \ m)]^{(X/11 \ m)} \quad (2)$$
In ACHA, the retrieved emissivity is always for the 11 μm channel and the retrieved β is always for the 11 and 12 μm channel. β can also be computed with knowledge of the single scattering properties. This allows for β values for any channel pair to be derived. When a sensor has no 12 μm channel, the β from the 11 and 12 μm channels can still be computed using the assumed microphysical models.

**OPTIMAL ESTIMATION**

The basic OE formulation used in Heidinger and Pavolonis (2009) is still used in ACHA. The OE attempts to derive a set of retrieved parameters (x) based on the observations (y) that minimize the cost. The cost function (Eq. 3) has two terms. The first is the deviation of x from its a priori constraint (x₀) and the second is the deviation of the y from the forward model estimate (f).

\[
(x - x_0)^T S_x^{-1} (x - x_0) + (y - f(x))^T S_y^{-1} (y - f(x))
\]  

(3)

Heidinger and Pavolonis (2009) provide the terms used in the 2-channel ACHA based on the 11 and 12 μm channels. This section provides the equations used in the 3-channel ACHA. In the 3-channel ACHA, the 11 μm channel is always used and the two-additional channels (X and Y μm) can be 6.7, 8.5, 12 or 13.3 μm. For GOES-13/15, ACHA uses the 6.7, 11 and 13.3 μm channels. For MTSAT, ACHA uses the 6.7, 11 and 12 μm channels. For VIIRS, ACHA uses the 8.5, 11 and 12 μm channels. For MODIS and MSG/SEVIRI, all of the 2 or 3-channel combinations listed above are possible. For the 3-channel ACHA, the observation vector (y) can be written as shown in Eq. (4) where BT is the brightness temperature and BTD is a difference in brightness temperatures.

\[
y = \begin{bmatrix} BT(11 \ m) \\ \vdots \\ BTD(11 \ Y \ m) \end{bmatrix} = \begin{bmatrix} T_c \\ e(11 \ μm) \\ β(12/11 \ μm) \end{bmatrix}
\]  

(4)

The vector of retrieved parameters (x) remains the same regardless of the number of channels used.

\[
x = \begin{bmatrix} T_{ef} \\ BTD(11 \ X \ m) \\ BTD(11 \ Y \ m) \\ e(11 \ μm) \end{bmatrix}
\]  

(5)

The 3-channel Jacobian or Kernel matrix (K) for the 3-channel ACHA is shown in Eq. (6).

\[
K = \begin{bmatrix} \frac{BT(11 \ m)}{T_{ef}} & \frac{BT(11 \ m)}{e(11 \ m)} & \frac{BT(11 \ m)}{(12/11 \ m)} \\ \frac{BTD(11 \ X \ m)}{T_{ef}} & \frac{BTD(11 \ X \ m)}{e(11 \ m)} & \frac{BTD(11 \ X \ m)}{(12/11 \ m)} \\ \frac{BTD(11 \ Y \ m)}{T_{ef}} & \frac{BTD(11 \ Y \ m)}{e(11 \ m)} & \frac{BTD(11 \ Y \ m)}{(12/11 \ m)} \end{bmatrix}
\]  

(6)

The element of K that relates the derivative of a BTD to the cloud temperature is shown below. Channel X is shown in these examples but the expressions for channel Y are the same.

\[
\frac{BTD(11 \ X \ m)}{T_c} = \frac{BT(11 \ m)}{T_c} - e(X \ m) T(X \ m) \frac{B(X \ m)}{T_c} - \frac{B(X \ m)}{T_c}
\]  

(7)
The expression of the derivative of a BTD to the cloud emissivity is given in Eq. (8).

\[ \frac{\text{BTD}(11 \text{ m})}{e_c(11 \text{ m})} = \frac{\frac{\text{BT}(11 \text{ m})}{e_c(11 \text{ m})} [R_{\text{clt}}(X \text{ m}) R_{\text{cl}}(X \text{ m})][ (X/11 \text{ m})(1 e_c(11 \text{ m}))^{(X/11 \text{ m})} ]}{\frac{B(X \text{ m})}{T}} \]

The derivative of a BTD to the 11/12 μm β is given in Eq. (9).

\[ \frac{\text{BTD}(11 \text{ m})}{(12/11 \text{ m})} = \]

\[ [R_{\text{clt}}(X \text{ m}) R_{\text{cl}}(X \text{ m})][ (X/11 \text{ m})(1 e_c(11 \text{ m}))^{(X/11 \text{ m})} ] \]

\[ \frac{\frac{\text{BT}(11 \text{ m})}{e_c(11 \text{ m})} [R_{\text{clt}}(X \text{ m}) R_{\text{cl}}(X \text{ m})][ (X/11 \text{ m})(1 e_c(11 \text{ m}))^{(X/11 \text{ m})} ]}{\frac{B(X \text{ m})}{T}} \]

The values of \( \frac{(X/11 \text{ m})}{(12/11 \text{ m})} \) are computed using the regressions based on the single scattering properties of ice and water cloud particles. The values of \( e_c(X \text{ m}) \) are computed using Eq. (2).

**COVARIANCE COMPUTATIONS**

One new aspect of ACHA since the GOES-R baseline is the computation of the forward model covariance matrix \( (S_y) \). In the baseline, \( S_y \) was a diagonal matrix and the diagonal terms were based solely on the estimates of calibration and spatial errors. The new expression for \( S_y \) includes computations of the covariance of the different elements of \( y \) with each other based on clear-sky calculations. The clear-sky covariance is computed separately over several surface types (ocean, land, desert, snow, Arctic, Antarctic). The clear-sky covariance is multiplied by the cloud transmission to approximate the cloudy-sky values. The equation below shows the new formulation. The \( S_y(i,j) \) is the expression for a term on the diagonal and \( S_y(i,j) \) is the expression for an off-diagonal term.

\[ S_y(i, i) = \sigma^2 + \sigma^2_{\text{pat}} + (1 - \epsilon_c)^2 \text{cov}_{\text{clear-sky}}(y_i, y_i) \]  

\[ S_y(i, j) = (1 - \epsilon_c)^2 \text{cov}_{\text{clear-sky}}(y_i, y_j) \]  

The main benefit of this formulation over the original diagnostic formulation is that the OE uncertainties are lower and more realistic (see Figure 5).

**MODIFICATIONS FOR AMV APPLICATIONS**

The assignment of the height of wind vectors derived from cloud motion is a challenging problem. The GOES-R AMV Team decided to collaborate with the GOES-R Cloud Team and replace their traditional height assignment methods and use the output of ACHA. One of the challenging issues is the reliance of AMV applications on the height results at cloud edges. Cloud edges are often optically thin and heterogeneous. Both of these issues can degrade the cloud height performance. In recognition of this issue, the ACHA algorithm has undergone several modifications to improve edge performance. To illustrate this issue, Figure 1 shows a result from GOES-14 during Hurricane Sandy. The image on the bottom shows a cross section of the cloud layers from the NASA CALIPSO/CALIOP 1km Cloud Layer Products. The grey regions denote the cloud layer from CALIOP. The upper black line is the Tropopause and lower blue line is the surface. The inset figures show a map (left), a false color image
and the ACHA product (right). The red line in the insets is the CALIPSO track. The colored points give the ACHA result and the color denotes the emissivity (color bar on right). Figure 1 does not show ACHA results, it shows the cloud height derived from assuming a black-body (emissivity = 1) cloud. This method calculates the height using a NWP profile lookup with the observed 11 µm brightness temperature. Note that this simple method fails drastically near the cloud edge since the true cloud emissivity becomes very low.

In the original ACHA, the a priori OE constraint on the cirrus height was taken from an offset from the Tropopause height and this offset was chosen based on a global climatology. For any particular situation, this can be significantly off. Because thin cirrus are reliant on the a priori value, this can damage the performance near cloud edges. Figure 2 illustrates this by showing the ACHA results that use the original cirrus height a priori. In this case the a priori is too high and this causes the ACHA heights to be overestimated and chaotic in the thinner regions of the cloud.

The main improvement has been achieved through the use of a background cirrus temperature field. This field is obtained by identifying cirrus results whose emissivity is greater than 0.7. Cirrus with emissivities greater than 0.7 are observed to be accurate compared to CALIPSO. As Figure 1 shows, cirrus heights show very little variation over large horizontal scales. In ACHA, the thicker cirrus results are spatially averaged at a scale of 250 km to provide a background cirrus field that is used as the a priori O.E. constraint for the thinner cirrus. Figure 3 shows the results of the use of the cirrus background. Note that many of the ACHA results (see latitude = 29°) for the thinner cirrus are now falling within the CALIPSO values.

The last modification made to ACHA involves the use of the O.E. cost as a filter. As Figure 3 shows, even with a better height a priori value, some retrievals are still inaccurate. This can happen when multi-layer situations exist, but are undetected or the assumed cloud phase is wrong. The O.E. cost includes a term of how well the observations matched the forward model. When ACHA accuracy suffers, this corresponds to retrievals with a higher final cost. The cost is a non-dimensional number and a typical value for convergence is the dimension of the x-array, which in ACHA’s case is 3. Figure 4 shows the impacts of imposing a threshold of 2 on the cost. As this figures shows, this eliminates those erroneous overestimations. The cost is an output of ACHA and AMV applications can apply any filter they find useful.

Figure 1: Comparison of GOES-14 ACHA with CALIPSO CALIOP on September 27, 2012 at 07:30 UTC over Hurricane Sandy. The image on the bottom shows a cross section of the cloud layers from the NASA CALIPSO/CALIOP 1km Cloud Layer Product. The grey regions denote the cloud layers from CALIOP. The upper black line is the Tropopause and lower blue line is the surface. The inset figures show a map (left), a false color image (middle) and the ACHA product (right). The red line in the insets is the CALIPSO track. The colored points give the ACHA result and the color denotes the cloud emissivity (color bar on right). X symbols denote pixels treated as ice phase and circles denote water phase pixels. This figure shows a retrieval using only the 11 µm channel and assuming an opaque cloud.
Figure 2: Same as Figure 1 except results are for ACHA using 6.7, 11 and 13.3 µm channels. No cirrus background field is used in the height a priori constraint.

Figure 3: Same as Figure 2 except a cirrus background field is used in the height a priori constraint.

Figure 4: Same as Figure 3 except a threshold of 2 is placed on the maximum OE cost value.
PERFORMANCE EVALUATION

This section presents an evaluation of the performance of ACHA relative to the CALIPSO CALIOP 1km Cloud Layer Product. The goal of this analysis is to compare the ACHA performance for GOES-R and VIIRS. VIIRS differs from the geostationary imagers in that it offers no IR channels in the atmospheric absorption bands ($H_2O$ or $CO_2$). The impact of this spectral information to an ACHA like algorithm is discussed in Heidinger et al. (2010). To accomplish this analysis, a full day of AQUA/MODIS data was processed. MODIS has the advantage of providing all channels needed for this comparison and is flown in formation with CALIPSO, which guarantees global coverage of this analysis.

Each of these results is shown as a 2-d histogram with the x-axis being the cloud emissivity and the y-axis being the cloud height. The values used here are the ACHA, not the CALIPSO values. These two parameters are the dominant drivers in the ACHA performance. These histograms are a useful diagnostic tool. The means are computed for all bins. The line-plots show the mean values along each column and row.

Figure 5 shows a comparison of the ACHA height uncertainties (left) compared with the CALIPSO errors. The ACHA height uncertainties come from the OE diagnostics. The CALIPSO errors are computed as the mean magnitude of the ACHA-CALIPSO height values. Figure 5 shows these two metrics roughly agree in magnitude and distribution in the 2-d histograms. This agreement indicates that OE covariance metrics are realistic since they determine the OE uncertainties. The lowest errors are seen for thicker clouds (emissivity > 0.7) and the highest errors are for thin cloud (emissivity < 0.4). The higher uncertainties for CALIPSO for very thin clouds are likely due to cloud phase errors, which ACHA cannot easily recover from.

![Figure 5: Comparison of cloud height uncertainties (left) with the ACHA-CALIPSO differences (right).](image)

Figure 6 shows the distribution of the cloud height biases derived from the MODIS data processed using ACHA in a GOES-R mode (left) and a VIIRS mode (right). The absolute value of the mean biases is quite close. The VIIRS biases tend to be larger for thin clouds than GOES-R. The GOES-R biases are more negative for opaque clouds. Both show large errors for some very low clouds with moderate emissivities. These are likely actually cirrus clouds that are typified. These clouds are relatively rare. Note that these differences are much less than the uncertainties shown in Heidinger et al. (2010). That paper considered only the sensitivity changes due to the spectral information. A real algorithm like ACHA that employs many a priori constraints and spatial analysis can offer ways to reduce the impact of missing spectral data.
Figure 6: Comparison of cloud height biases derived from MODIS data processed using ACHA in the GOES-R mode (left) and with a VIIRS mode (right).

Figure 7 shows an attempt to map the cloud height differences into wind speed differences. The wind speed errors are computed as the difference in the window at the ACHA height minus the wind speed at the CALIPSO height. The GOES-R results show a general improvement over those from VIIRS though the overall mean bias in the wind speed is similar (-0.57 to 0.8 m/s). The vertical profile of wind speed bias show that GOES-R has a more uniform distribution while VIIRS has a definite shape.

Figure 7: Same as Figure 6, except the comparison is with estimated wind speed biases from ACHA.

CONCLUSIONS

ACHA is continuing to evolve from the baseline GOES-R ABI cloud height algorithm developed in 2009. It supports many of the current geostationary and polar orbiting imagers. In addition, it has been modified to improve its performance for AMV applications. This paper presents the mathematics
needed to extend the 2-channel ACHA to the 3-channel form used on most current imagers. The new off-diagonal covariance expressions are presented and shown to generate uncertainty estimates that are similar to those derived from CALIPSO. A new technique involving spatial processing to improve cirrus edge performance was shown and demonstrated. Lastly, a global analysis was shown using MODIS to simulate GOES-R and VIIRS observations. The GOES-R results were shown to be generally better than VIIRS in terms of height bias and in terms of wind-speed bias.

REFERENCES

