

MEASURING THE ERROR BETWEEN ACTUAL AND ESTIMATED ATMOSPHERICS AND THE EFFECT ON ESTIMATING REFLECTANCE PROFILES

Allan W. Yarbrough, Michael J. Mendenhall, and Steven T. Fiorino

Air Force Institute of Technology
Dept of Electrical and Computer Engineering
Dept of Engineering Physics
2950 Hobson Way, Wright-Patterson AFB, OH 45433

1. INTRODUCTION

Atmospheric absorption of electromagnetic energy is a problem across the broader topic of remote sensing. Atmospheric scientists have spent a great deal of effort to characterize the atmosphere, estimate atmospheric parameters from data, and generate methodologies for removing those atmospheric effects (e.g., empirical line correction [1] [2] and MODTRAN [3], to name a few). Although many of the techniques for estimating atmospheric parameters and removing atmospheric effects from imagery have been very successful, there is a level of uncertainty in the estimates that are still unaccounted for on reconstructed data.

This article provides a brief look at how the error in the estimate of the atmospheres affects the reconstruction of a hyperspectral image (i.e., going from sensor-reaching radiance to estimated reflectance and working in the illumination-neutral reflectance environment). To this end, we first investigate and develop distance measures between atmospheric profiles. This is a non-trivial problem, as it is currently unknown what the differences between atmospheric profiles really mean and how two distances with the same numerical value may affect the estimated reflectance of a hyperspectral signature. That is to say, different pairs of atmospheric profiles with the same measured distance between them may not have the same effect on the error in their target signature, and therefore the relationship is likely one-to-many and not necessarily one-to-one. As such, one must carefully choose how the input error (input being the atmospheric profile) is represented.

The second aspect of this paper is the mapping between input error (how far off is the estimated atmospheric profile from the actual atmospheric conditions under which the targets of interest were imaged) and the output error (the error as measured by the Euclidean distance between the calculated reflectance spectrum of a target under the true atmospheric profile and that of a target under the estimated atmospheric profile).

The importance of a good definition of a distance between two atmospheres can not be understated. It is a precursor to better understanding the effects of atmospheric estimation error on other processes such as Change Detection, target detectors such as the Adaptive Matched Filter [4] or Adaptive Cosine Estimator [4], and other algorithms such as the Normalized Difference Vegetation Index (NDVI) [5] used in vegetation health analysis.

2. DISTANCES BETWEEN ATMOSPHERES

There are two general approaches to defining a distance between atmospheres. A first approach is to measure the distance between two solar irradiance curves defined by a blackbody radiator (the sun) transmitting through an atmospheric profile. A second approach is to consider the difference between the profiles themselves. How are atmospheric profiles characterized? The most significant and widely recognized approach is to characterize the atmosphere by the water vapor content of the atmosphere. Several measures of water vapor content exist: absolute humidity, water vapor mixing ratio, relative humidity, and others.

The values described vary as a function of altitude, which gives a good argument to consider a weighting factor in the distance measurement between the profiles themselves. Preliminarily, we describe the distance between atmospheres as the Euclidean distance between the measures of two parameters that describe the profile taken at four radiosonde layers. In particular, we use the water vapor mixing ratio w_1 (in grams of H_2O per kilogram of all other gasses) and absolute humidity ρ (grams of H_2O per cubic centimeter) because these measures of water vapor are the most independent. (Relative humidity, for example, is dependent on both temperature and pressure.) These two distances are shown in Eqn. 1 and Eqn. 2, where $z_i \in \{0m, 500m, 1000m, 1500m\}$ and $\{a_1, a_2\}$ are the two atmospheric profiles being compared. Preliminary results are presented in Section 4 using this methodology.

$$d(a_1, a_2) = \sqrt{\sum_{i=1}^4 (w_1(a_1, z_i) - w_1(a_2, z_i))^2} \quad (1)$$

$$d(a_1, a_2) = \sqrt{\sum_{i=1}^4 (\rho(a_1, z_i) - \rho(a_2, z_i))^2} \quad (2)$$

The distance between profiles is expanded to include the atmospheric density effect as described in [6]. The concept is that the magnitude of the effect on the transmission of the water vapor content of a particular atmospheric level is a function of the density effect. The transmittance $t(z)$, or the ratio of the radiation reaching the target to the radiation incident on the top of the atmosphere as a function of the target altitude z is an integral resulting in

$$t(z) = \exp \left[-\frac{k_a w_1 \rho_0 H}{\mu} \exp\left(-\frac{z}{H}\right) \right] \quad (3)$$

where w_1 is the constituent mixing ratio, k_a is the mass absorption coefficient, ρ_0 is the maximum density at sea level, μ is the cosine of the zenith angle, and H is the scale height (around 8km, the altitude at which the density is $e^{-1} = 36\%$ of its value at sea level). Due to the rules of integration, one can divide the integral into the four target altitudes, which using Eqn. 2 yields a weighting of

$$d(a_1, a_2) = \sqrt{\sum_{i=1}^4 \Delta t(z_i) (\rho(a_1, z_i) - \rho(a_2, z_i))^2}, \quad (4)$$

where $\Delta t(z_i) = t(z_i) - t(z_{i+1})$

The remainder of the work will explore this new density-weighted distance between profiles, comparing it to those defined in Eqns. 1 - 2.

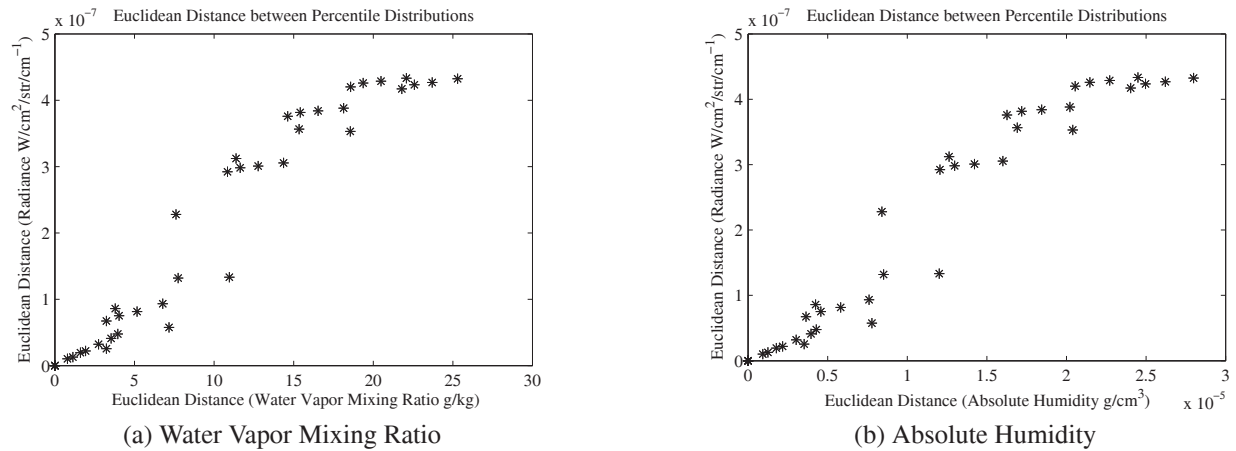


Fig. 1. (a) Plot of the Euclidean Distance measure between all nine percentile measurements of water vapor mixing ratio (x -axis) and the corresponding Euclidean Distances between the radiance spectra (y -axis). The points have a correlation coefficient of 0.959. (b) Plot of the Euclidean Distance measure between all nine percentile measurements of absolute humidity (x -axis) and the corresponding Euclidean Distances between the radiance spectra (y -axis). The points have a correlation coefficient of 0.960.

3. EXPERIMENTATION

The atmospheric profile data are taken from the Laser Environmental Effects Distribution Reference (LEEDR) [7]. These data were collected from radiosonde measurements at multiple sites across the world. They are grouped by the month, time of day, and - most significantly - the percentile in which they fall in a distribution correlated to relative humidity. For the purposes of this paper, we will consider atmospheric profiles taken at nine different percentiles of the distribution: 1%, 5%, 10%, 20%, 50%, 80%, 90%, 95%, and 99%.

The profiles taken at these distributions become user-defined atmospheres used by MODTRAN to generate the sensor-reaching radiance for a target of a spectrally independent surface albedo of one. The scene geometry is of a sensor at an altitude of 3048m with a nadir zenith angle imaging a target on the surface at 300m MSL. The image is collected at 1:00 p.m. EDT on June 1, 2001 at a location of 43°E, 77°W.

4. PRELIMINARY RESULTS

Results are presented in Fig. 1 where the x -axis is the Euclidean distance between the estimated reflectance of the target signatures generated with the imaged atmosphere and an incorrect atmosphere. The y -axis is the error between the imaged atmosphere and the incorrect atmosphere. These results show high levels of correlation between the atmospheric profile estimation error and the difference between the resulting radiance spectra.

5. CONCLUSIONS

For our final paper, we will accomplish two things. First, we will submit the measures shown above for the four reflectance spectra shown in Fig. 2: cropland, galvanized steel, deciduous tree, and olive paint. These spectra emphasize different portions of the wavelengths they span. We will evaluate how these different reflectance spectra improve or degrade the correlation between the error measure for the atmospheric profile pairs and the error measure for the radiance spectra. The variation in target signatures will give us a better idea of how the error in the estimate of the atmospheric conditions affects broad categories of imaged targets. Second, we will evaluate weighting functions for the different radiosonde altitudes and how these effect the correlation.

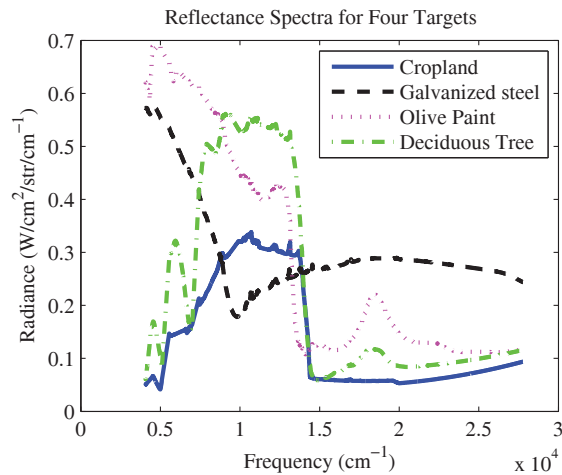


Fig. 2. Reflectance plots of four target signatures: cropland, galvanized steel, deciduous tree, and olive paint

6. REFERENCES

- [1] Berk, A. and Bernstein, L.S. and Robertson, D.C., "Modtran: A moderate resolution model for LOWTRAN 7," April 1989, GL-TR-89-0122.
- [2] Berk, A. and Bernstein, L.S.; Anderson, G.P.; Acharya, P.K.; Robertson, D.C.; Chetwynd, J.H.; Adler-Golden, S.M., "MODTRAN cloud and multiple scattering upgrades with application to AVIRIS," *Remote Sensing of the Environment*, vol. 65, pp. 367–375, 1998.
- [3] Karpouzli, E. and Malthus, T., "The empirical line method for the atmospheric correction of IKONOS imagery.," *International Journal of Remote Sensing*, vol. 24, pp. 1143–1150, 2003.
- [4] Manolakis, D. and Shaw, G., "Detection algorithms for hyperspectral imaging applications," *IEEE Signal Processing Magazine*, vol. 19, no. 1, pp. 29–43, Jan 2002.
- [5] Colwell, J. E., "Vegetation canopy reflectance," *Remote Sensing of the Environment*, vol. 3, no. 3, pp. 175–183, 1974.
- [6] G.W. Petty, *A First Course in Atmospheric Radiation (2nd Edition)*, Sundog Publishing, 2006.
- [7] S.T. Fiorino and R. Bartell and M. Krizo and G. Caylor and K. Moore and T. Harris and S. Cusumano, "A first principles atmospheric propagation and characterization tool: the laser environmental effects definition and reference (LEEDR)," in *SPIE Proceedings*, vol., pp., 122–124.