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# Lecture 29. Na Doppler Lidar – Data Retrieval, Lidar Simulation, and System Optimization

- Data retrieval procedure vs. lidar setup
- STAR Na Doppler lidar simulation
- □ STAR lidar optimization

#### Data Inversion - Solving Lidar Equations

□ Lidar data inversion deals with the problems of how to derive meaningful physical parameters from raw data.

Raw data are usually a column or a row of photon counts, where the positions of photon counts in the column or row mark their time bins, thus the ranges or heights.

Data inversion is basically a reverse procedure to the development of lidar equation, i.e., solving the lidar equations to derive unknowns.

□ For Na layers in the MLT region, three main unknown parameters: Temperature, wind and Na density. Therefore, by the minimum, three equations are required to derive three unknowns, which is the basic idea for 3-frequency Na Doppler wind and temperature lidar. The Maui data given in the homework projects were taken by such a lidar.

□ It is necessary to understand the detailed physical procedure from light transmitting, to light propagation, to light interaction with objects, and to light detection, in order to conduct data inversion correctly.



CU-BOULDER, SPRING 2011





#### **PMT+Discriminator Saturation Correction**





# Na Doppler Lidar at Maui



#### **UIUC Large-Aperture Steerable Na Doppler Lidar**



## Na Doppler Lidar Receiver



#### **Chopper Function - Transmission**

□ Chopper function is measured and then used to do chopper correction for lower atmosphere signals



## Main Process Step 1: Starting Point & Deriving T and V<sub>R</sub>

- 1. Extinction (Tc) at the bottom of Na layer is 1
- 2. Calculate the normalized photon count for each frequency

$$N_{Norm}(\lambda, z) = \frac{N_S(\lambda, z) - N_B}{N_S(\lambda, z_R) - N_B} \frac{z^2}{z_R^2} \frac{1}{T_c^2(\lambda, z)} - \frac{n_R(z)}{n_R(z_R)}$$

3. Based on the normalized photon counts, you get  $R_{\rm T}$  and  $R_{\rm W}$ 

$$R_{T} = \frac{N_{Norm}(f_{+}, z) + N_{Norm}(f_{-}, z)}{N_{Norm}(f_{a}, z)} \qquad R_{W} = \frac{N_{Norm}(f_{+}, z) - N_{Norm}(f_{-}, z)}{N_{Norm}(f_{a}, z)}$$

4. Estimate the temperature and wind using the calibration curves computed from physics (iteration vs. look-up table)

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#### Iteration vs. Look-up Table

□ Look up these two ratios on the calibration curves to infer the corresponding Temperature and Wind from isoline/isogram.



LIDAR REMOTE SENSING



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## Main Process Step 2: Bin-by-Bin Procedure & Loop

- 5. Calculate the Na effective cross section using temperature and wind derived.
- Using the effective cross-section and Tc = 1 (at the bottom), calculate the Na density using peak frequency signal or weighted 3-frequency signals.
- 7. From effective cross-section and Na density, calculate the extinction for the next bin.

$$T_{c}(\lambda, z) = \exp\left(-\int_{z_{bottom}}^{z} \sigma_{eff}(\lambda, z) n_{c}(z) dz\right) = \exp\left(-\sum_{z_{bottom}}^{z} \sigma_{eff}(\lambda, z) n_{c}(z) \Delta z\right)$$

8. Loop through to repeat the procedure for the next bin for normalized counts, T and  $V_R$ , and Na density, until reaching the end of the Na layer.



# Na Density Derivation

□ The Na density can be inferred from the peak freq signal

$$n_{Na}(z) = \frac{N_{norm}(f_a, z)}{\sigma_a} 4\pi n_R(z_R) \sigma_R = \frac{N_{norm}(f_a, z)}{\sigma_a} 4\pi \times 2.938 \times 10^{-32} \frac{P(z_R)}{T(z_R)} \cdot \frac{1}{\lambda^{4.0117}}$$

□ The Na density can also be inferred from a weighted average of all three frequency signals. The weighted effective cross-section is defined as

$$\sigma_{eff_wgt} = \sigma_a + \alpha \sigma_+ + \beta \sigma_-$$

where  $\alpha$  and  $\beta$  are chosen so that

$$\frac{\partial \sigma_{eff\_wgt}}{\partial T} = 0; \qquad \frac{\partial \sigma_{eff\_wgt}}{\partial v_R} = 0$$

This method is to make the weighted effective cross-section insensitive to T and  $V_R$ , in order to minimize the Na density errors caused by the errors in derived T and  $V_R$ .

□ The Na density is then calculated by

$$n_{Na}(z) = 4\pi n_R(z_R)\sigma_R \frac{N_{norm}(f_a, z) + \alpha N_{norm}(f_+, z) + \beta N_{norm}(f_-, z)}{\sigma_a + \alpha \sigma_+ + \beta \sigma_-}$$

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## **STAR Lidar Simulation Results**

See MatLab code demonstration

For very moderate lidar pulse energy (16.7 mJ/pulse), relatively low receiver efficiency (80% reflectivity at 589 nm for primary and secondary mirrors, respectively) and the 40-cm diameter true-Cassegrain telescope, the simulation results show that

- (1) Rayleigh sum of 300 shots for 25–35 km is about 26,900 counts
- (2) Rayleigh sum of 300 shots for 30–40 km is about 9,100 counts
- (3) Na signals of integration through the entire Na layer is about 150 count/shot.

#### **STAR Lidar Receiver Optimization**

□ Signal strength increased by a factor of 4–5 times from September 2010 to March 2011. It was achieved by much more precise alignment of the telescope and receiver chain.



#### **STAR Lidar Receiver Optimization**

□ Similar as above, except Rayleigh is from 30-40 km range



□ The Na signals have reached 80 counts/shot for the STAR lidar with a receiver consisting of a 40-cm telescope.