Estimation of Lidar 1064 and 532 nms aerosol backscatter using Ceilometer 910nm and Artificial Neural Network

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ABSTRACT

The Lidar is a remote sensing system used in research to provide an atmospheric backscatter power profile of suspended aerosols (particles) and molecules. The 3 wavelength Lidar system at UPRM witch enables the determination of many atmospheric parameters is not designed to operate during the drizzling and rain events, hence it is turned off. As a result, there are time intervals with no Lidar data (data gaps). The lack of power data continuity affects the continuity of all of the important parameters to be calculated which depend on Lidar data, consequently either directly or indirectly affect the results of the Regional Atmospheric Simulation algorithms in their ability to predict the desired events, such as rain. To solve this problem an Artificial Neural Network (ANN) was developed to generate the missing data gaps for 1064nm and 532 nm Lidar profiles using 910nm data for the same time and range from the all weather Ceilometer in-situ with the 3 wavelength Lidar. Results of the error analysis show a good match of better than 0.9 correlation and 0.52 RMSE values for the Sept. 4, 2014 data from 0.5km to 2km range.

INTRODUCTION

The UPRM Lidar system consist of an industrial three wavelengths (355, 532, and 1064nms) Brilliant B Laser at 14 Watts, a 20 inch telescope, and a sequence of optics that separate the received atmospheric backscatter into multiple wavelengths of 355, 387, 532, and 1064 nms. 20Hz pulses of laser beam are transmitted vertically, co-axial to the telescope, out into the atmosphere, and reflected light power is received and various atmospheric parameters are calculated and saved. A subsystem of optics are responsible in separating the received beam into a set of wavelengths 355, 532, and 1064nms. Sensors receive the incoming photons at the specific wavelengths, and signal processing subsystem in conjunction with LabView software provide the atmospheric profile for each wavelength which are stored and displayed on a desktop computer. Ceilometer is a single wavelebgth transmit/receive, eye safe, all weather, Lidar providing atmospheric backscatter power profile at 910nm.

Artificial Neural Network

A Neural Network is a statistical learning algorithm to estimate or approximate a function by adjusting the values of weight (w) and bias (b) between the elements. In this research, the NN selected has 150 inputs that correspond to the aerosol backscatter from Ceilometer at a wavelength of 910 nm from 0.5 to 2 km above the ground, with a 10 meter resolution. The Output of the Neural Network is the estimated Lidar aerosol backscatter at a wavelength of 1064 nm for the same range and time frame as Ceilometer 910 nm. The network contains a hidden layer of 24 neurons with a Log-Sigmoid transfer function, and an output layer of 150 neurons with a linear transfer function, as shown in figure 1. The network was trained with the back propagation Levenbergh-Mardquat method and a gradient descent with a momentum learning function that prevents the NN get stuck in shallow local minimum. To improve the NN training and results, a Gaussian filter is used in the ceilometer data to smooth the 910 nm raw aerosol backscatter data.

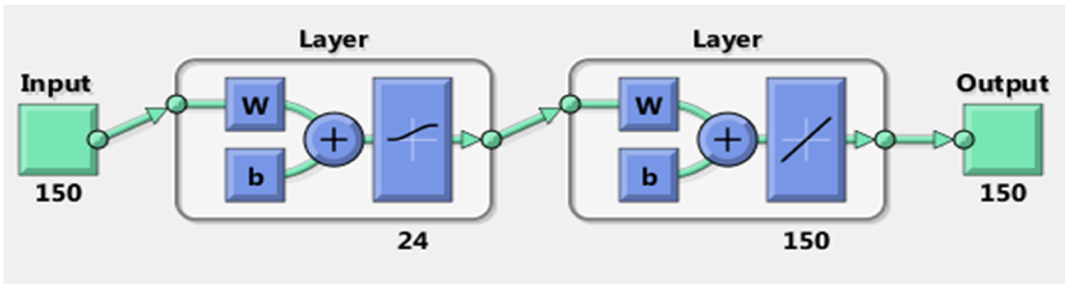
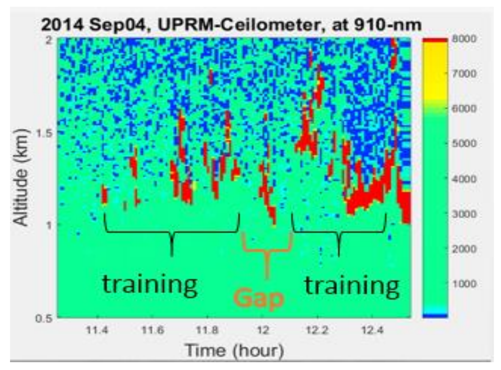


Figure 1: Network Architecture

Training of the Neural Network



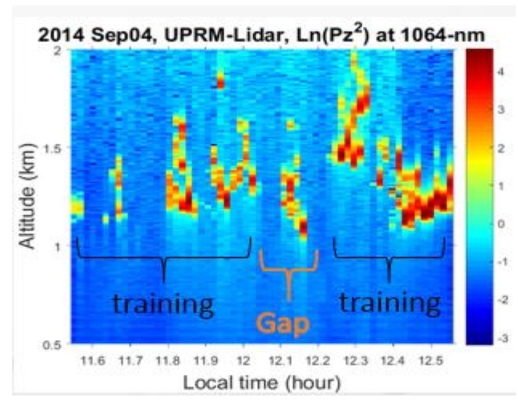
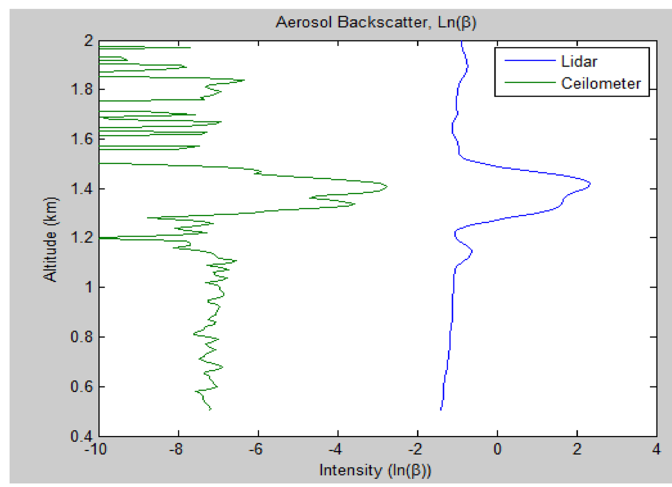


Figure 2: 910nm NN input data, gap data is not used in the training

Figure 3: 1064nm NN output data, gap data is not used in the training

RESULTS



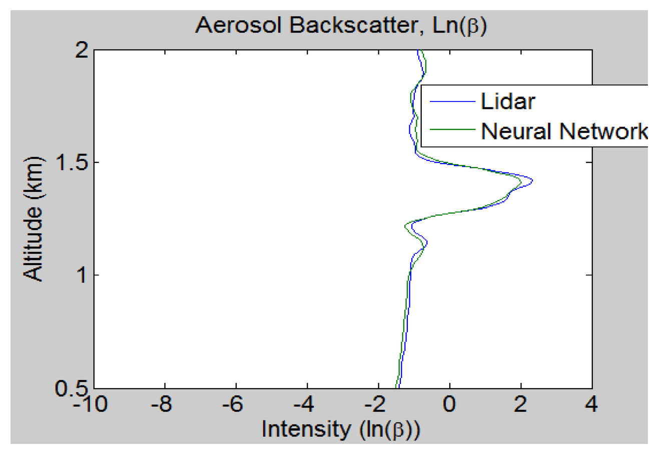
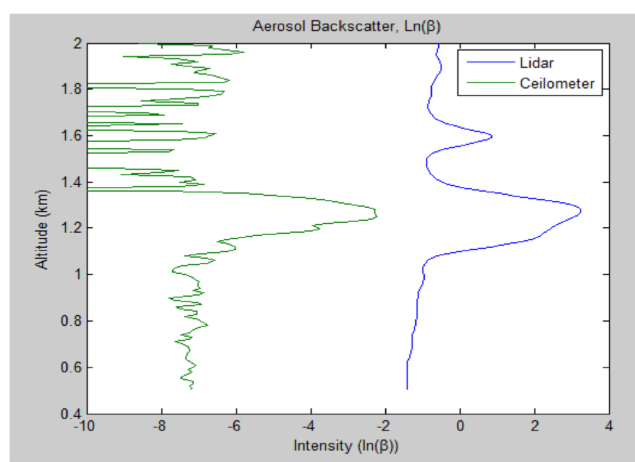


Figure 4: One column data from Ceilometer and Lidar Aerosol backscatter from 0.5 km to 2 km. Blue plot is the Lidar 1064 nm backscatter and the green plot is the Ceilometer 910 nm raw backscatter data of the same range and time.

Figure 5: Validation of trained NN. Blue plot is the real Lidar backscatter and green plot is the NN output approximating a 1064 nm backscatter for a Ceilometer 910 nm backscatter, using <u>training set of samples only.</u> Matching error in terms of correlation and RMSE were 0.99 and 0.16, respectively.



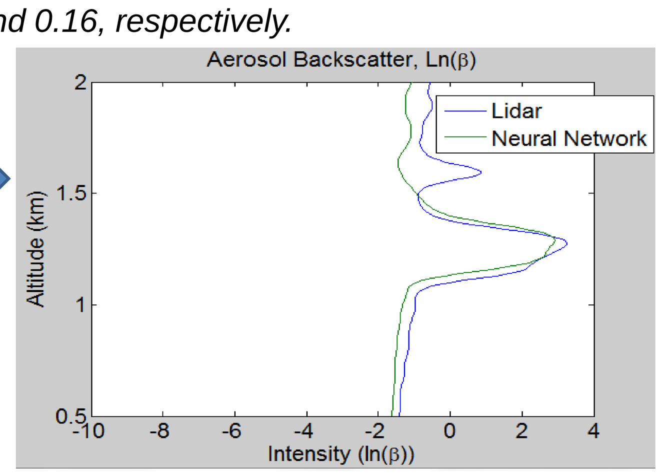


Figure 6: One column data from Ceilometer and Lidar Aerosol backscatter, from 0.5 km to 2 km. Blue plot is the real Lidar 1064 nm backscatter and the green plot is the Ceilometer 910 nm raw backscatter data of the same range and time.

Figure 7: Matching between the Lidar and Neural Network estimation with a correlation of 0.96 and a RMSE of 0.41 after eliminating the outlier which was found at about 1.6 km. Blue plot is the Lidar backscatter, green plot is the NN output, approximating a 1064 nm backscatter from a Ceilometer 910 nm backscatter data which is <u>not within the training set of samples</u>.

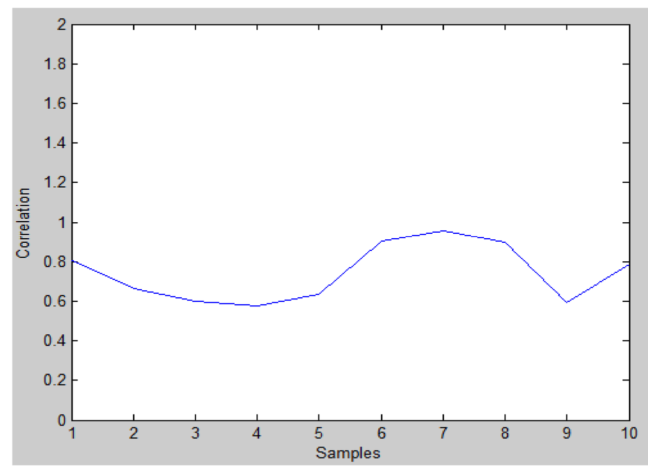


Figure 8: Correlation between the Lidar and Neural Network estimation for the 10 minutes gap which was not used in the training.

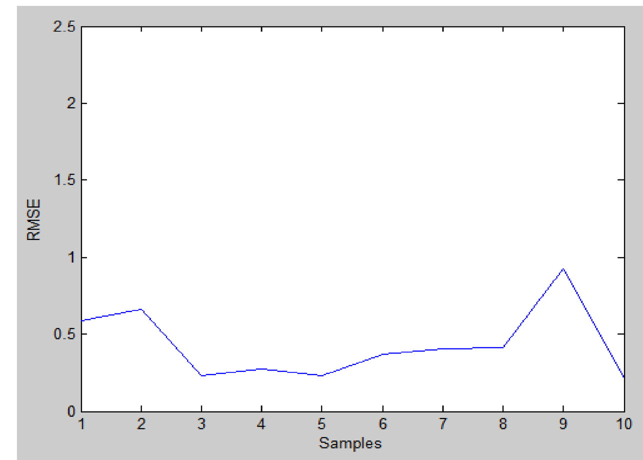


Figure 9: Root mean square error between the Lidar and Neural Network estimation for the 10 minutes gap which was not used in the training.

Neural Network Estimation of Lidar data gap for 532 nm profile

Neural Network of the same size and same number of hidden layers as before was trained to estimate 532 nm Lidar aerosol backscatter using ceilometer data for the same time and range. The Neural network input is defined by Ceilometer 910 nm aerosol backscatter data. The 532 nm data was used to train and test the neural network. The data selected was from September 4, 2014, from 0.5 to 2 km. NN training was done over 50 minutes of data, and 10 minutes was defined as gap. Matching error in terms of correlation and RMSE were 0.90 and 0.52, respectively. Figure 10 shows the plot of one column Lidar 532 nm and Ceilometer data. Figure 11 shows one column matching of 532nm Lidar data and the NN estimation., within the gap interval.

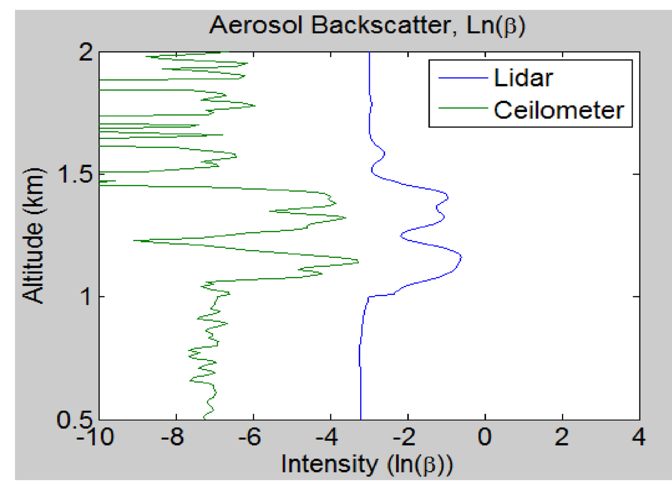


Figure 10: One column data from Ceilometer and Lidar Aerosol backscatter from 0.5 km to 2 km. Blue plot is the Lidar 532 nm backscatter data, and the green plot is the Ceilometer 910 nm raw backscatter data for the same range and time.

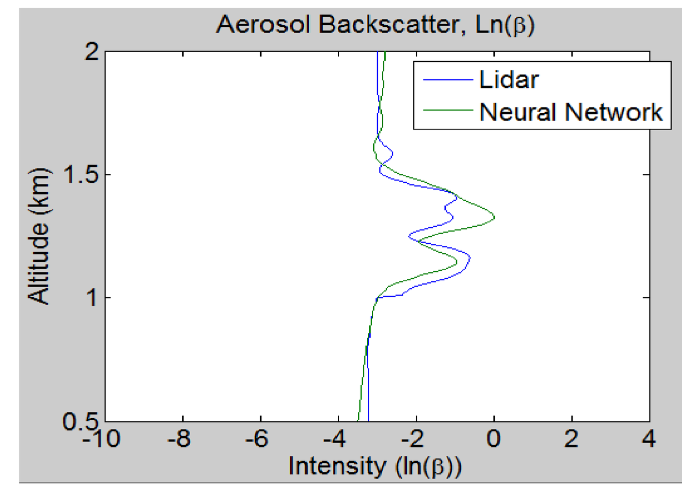


Figure 11: Matching between the Lidar and Neural Network estimation with a correlation of 0.90 and a RMSE of 0.52. Blue pot is the 532 nm Lidar backscatter and green plot is the NN output approximating a 532 nm backscatter for a Ceilometer 910 nm backscatter <u>not within the training set samples</u>.

Conclusion and Future Work

- •NN can estimate UPRM Lidar 1064nm and 532nm aerosol backscatter using known Ceilometer 910nm aerosol backscatter profile for the same range and time frame.
- ▪ Error analysis show a good match of better than 0.9 correlation and 0.52 RMSE values for the Sept. 4, 2014 data from 0.5km to 2km range, for both 532 and 1064nm estimations.
- •To improve NN and estimate longer gaps, more data is needed for training of the network..
- •Research is required to determine the variations of the numbers of neurons in the hidden layers as a function of gap length variations, and the effect on the NN accuracy.
- ▪ Estimation of gaps in the 355nm will be achieved in near future.

References

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Acknowledgments

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