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FINAL REPORT

LiDAR for Air Quality Measurement

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16. Abstract

The overall goal of this research is to investigate a unique light detection and ranging (LiDAR) technology for ambient air quality measurement of particulate matter. The ODU team has recently received a state-of-the-art elastic LiDAR from NASA Langley Research Center developed to measure aerosol vertical profiles. It was originally designed to be mounted on an aircraft. However, this sophisticated LiDAR can also be used on the ground to measure PM (particulate matter) in the air related to vehicle emissions. Several specific enhancement to the LiDAR hardware are performed to make it sensitive to PM classification.
The LiDAR system provides aerosols profile measurements by identifying the aerosol scattering ratio as a function of the altitude. The aerosol scattering ratios are used to obtain multiple aerosol intensive ratio parameters known as backscatter color ratio, depolarization ratio, and LiDAR ratio. The aerosol ratio parameters are known to vary with aerosol type, size, and shape. In this study, we employed LiDAR measurements to detect the source of the soot around the campus of Old Dominion University. Different ratio parameters including LiDAR ratio and color ratio are retrieved from collected data around the campus and employed for detection of soot aerosol around the campus. To find the source of soot in the measurements, a tracking algorithm is employed to track the source of the soot by tracking the concentration of that pollution in the data. Results of the implemented methods of quantifying and tracking soot in real data are presented in this study. The results show that the source of soot pollution in the study area is Hampton Blvd, a major street nearby the campus, where the volume of diesel trucks is relatively high since this corridor serves a major seaport in the city of Norfolk.

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1. Introduction

Aerosols play a crucial role in determining the radiation amount to the earth's atmosphere. Emissions from vehicles are one of the sources for aerosols (e.g. soot and smoke) that may be detected using remote sensing techniques such as a lidar [1]. Lidar is a powerful tool for atmospheric aerosol profiling because it resolves the vertical distribution of an atmospheric column [2]. The lidar system consists of a laser transmitter, a receiver and a data acquisition system [1]. The laser transmitter emits a pulse of light which is sent into the atmosphere. These light pulses from the laser encounters aerosols or particulate matter that may absorb or scatter and reflect the light back to the ground. A telescope focused at the same atmospheric volume as the transmitted laser pulse collects the backscattered light and then sends back to the receiver. The received signals are processed and averaged over 2 seconds before storing as aerosol profile resolutions. Once the data is stored, the signal retrieval is achieved [3-9] to obtain the optical parameters of the aerosol. In this study, the goal is estimating the source of soot in the region of campus of Old Dominion University (ODU) by using lidar to collect measurements of aerosols in that region. In planning of collecting data at the campus of ODU, we selected four points distributed close to Hampton Blvd. Hampton Blvd is the major road for diesel trucks in the area near campus and we expect that these trucks are the main source of soot close ODU area. The locations of the four selected sites for collecting data are shown in the map in Figure 1.

In this study, we first review methods of retrieval of aerosol parameters for purpose of detection through inversion solutions for processing lidar signals. The aerosols are then detected and classified based on the optical characteristics of aerosols which are encoded in the received backscattering. A Bayesian tracking algorithm using optical lidar parameters to track the source of soot in the data.

The rest of this study is organized as follows: In section 2, we describe Lidar system, Section 3 presents Optical parameters, Section 4 introduces the tracking algorithm, and the results are presented in Section 5. Section 6 concludes the study.

2. Lidar System Description

The LiDAR system used in this work consists of a laser transmitter, a receiver assembly, and data processing unit. The details of the hardware of the lidar is described in [10] and a schematic is shown in Figure 2. In a lidar system, a pulse of light is emitted from the laser, and as the beam travels through the atmosphere, it encounters particles (molecules, aerosols, water droplets, etc.) that scatter the light and reflect some of the laser beam back towards the ground. A telescope aimed at the same atmospheric volume as the laser pulse will capture the backscattered photons and collects the signal to an optical receiver. The lidar used at Old Dominion University is an elastic

LiDAR where the emission and the reception wavelengths are the same. The main applications of such lidar are monitoring pollution and aerosols to provide air quality measurements.

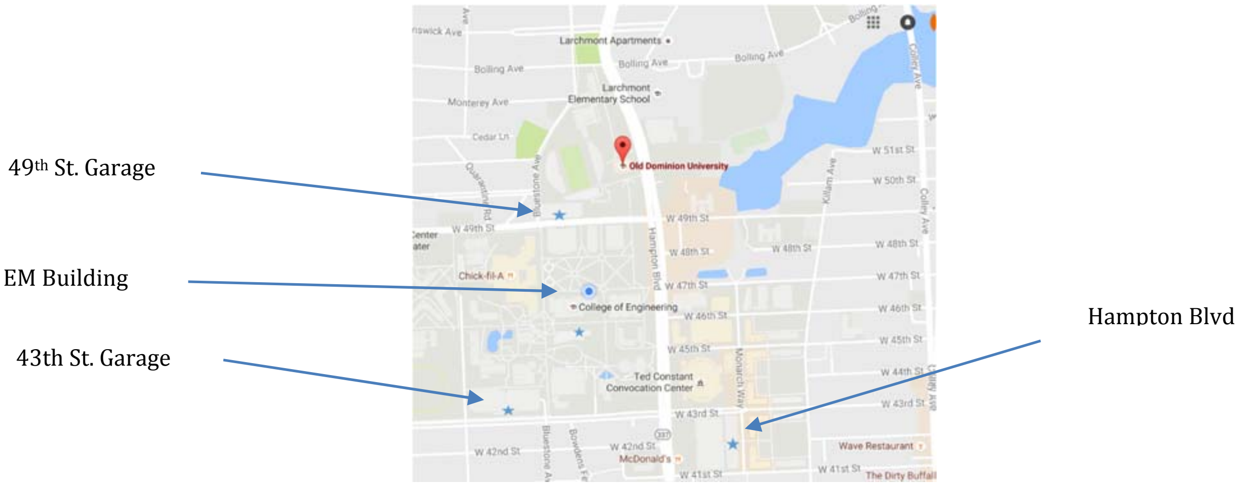


Figure 1. The locations of the selected points around Hampton Blvd near the campus of Old Dominion University. The locations are indicated by stars.

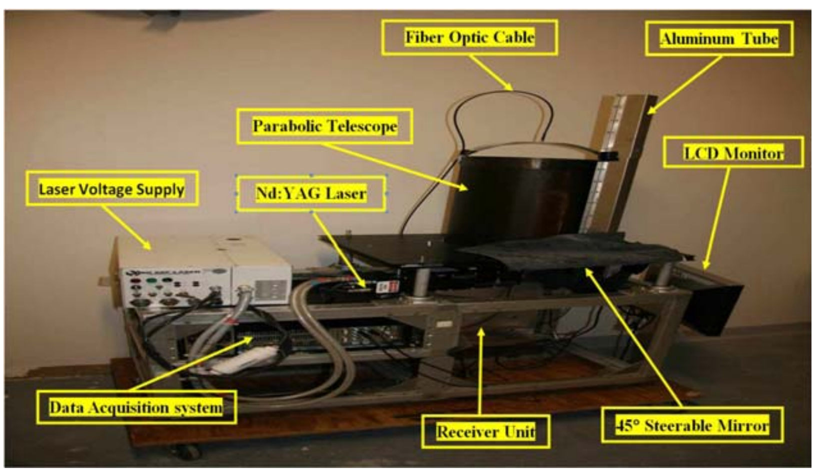


Figure 2. Lidar in Vision Lab at Old Dominion University

3. Aerosols Optical Parameters

In this study, we retrieve the backscattering color ratio and lidar ratio as optical parameters that encode the optical characteristics of the aerosols. We retrieve these optical parameters through inversion solutions for lidar signals. Lidar signal inversion methods require the use of one or more a priori assumptions that are selected according to the particular optical solution. The contrast between the various retrieval methods lie in the processes of determining boundary conditions and in the selection of a priori assumptions concerning other missing information. The fundamental inversion methods include the slope method [3], [4], Klett [5], [6], [7] and Fernald methods [8], [9].

4. Bayesian Tracking Algorithm

Source localization problem is especially difficult in a turbulent flow environment, such as the planetary boundary layer. Plume effluent in a turbulent wind spreads in a random manner, meandering to create patches of high and low concentration. The plume width and the concentration within the plume do not vary predictably in time or space. The uncertain relationship between the location of a detection and the location of the source in a turbulent flow makes source localization challenging.

Various algorithms have been proposed for the source localization problem, including gradient descent [15], biologically inspired approaches [16], and probabilistic methods [17].

We compared three algorithms for estimating an airborne contaminant in a turbulent wind field, using gradient descent algorithm, extended Kalman filter, and recursive Bayesian estimation algorithm [18]. By comparison, Bayesian estimation requires relatively weak modeling assumptions, and simulation results suggest Bayesian estimation is less sensitive to error in the initial state.

5. Results

This section presents the collected data and the results of the tracking algorithm. In this study, we collected data at four locations on the campus of ODU and are marked by stars as shown in Figure 1. Figure 3 shows the color and lidar ratios retrieved from the data collected at Hampton Blvd Garage location. The data are collected for more than one hour at each location and the lidar is placed on the roof of the Garages to ensure safety.

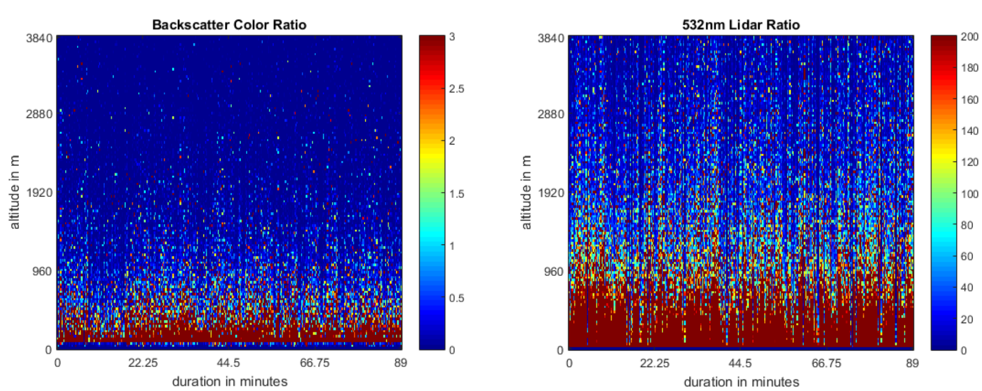
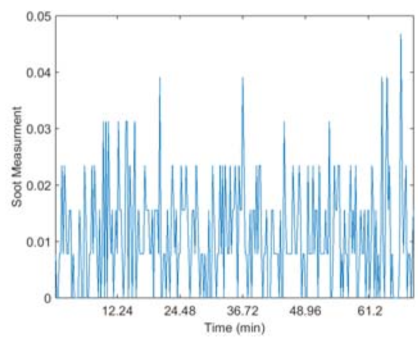


Figure 3. Color and lidar ratios of data collected at Hampton Blvd Garage.

We then implement a Bayesian tracking algorithm to track the source of soot in the area of the study. We use the values of color and lidar ratios [22-26] as ground truth to detect the soot at the locations of collecting the data. Once the soot is detected at these locations, we find the missing detection over a grid, which covers the area of study, by using the linear interpolation. For the purpose of interpolation, we first normalize the frequency of detection of soot for the four collecting sites. The results of the normalized frequency are shown in Figure 4.

Figure 5 shows the interpolated normalized frequency of soot by using the lidar ratio over the the area of study**.** We also obtain frequency of detection of soot by using the color ratio and then we normalize it and compute the interpolation over the same grid in the area of study. The normalized frequency of soot detection by using the color ratio is shown in Figure 6. Figure 7 shows the interpolation of the normalized frequency over the search grid.



(a) Hampton Blvd Garage

Figure 4. Normalized frequency of soot detection by using lidar ratio

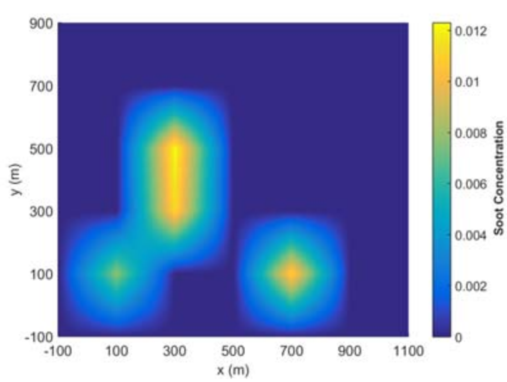
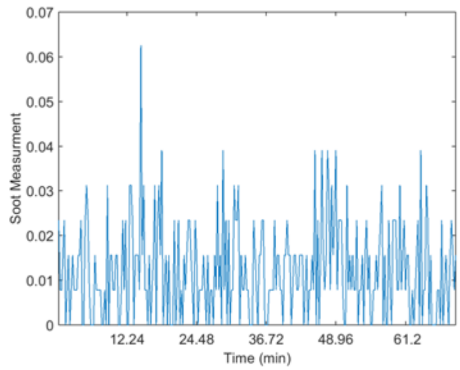


Figure 5. Interpolation of normalized frequency over search grid in the case of lidar ratio.



(a) Hampton Blvd Garage

Figure 6. Normalized frequency of soot detection by using color ratio

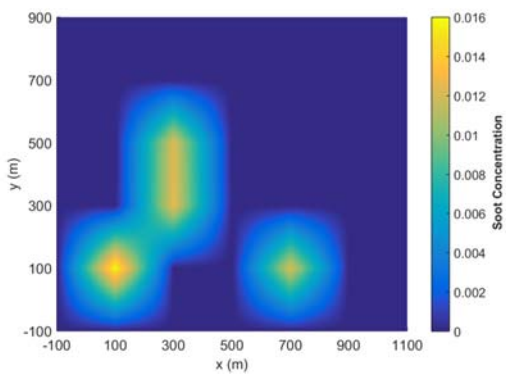
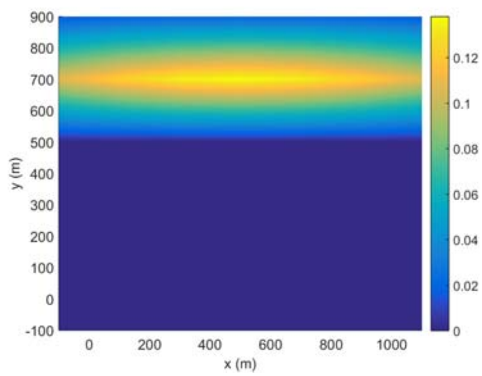


Figure 7. Interpolation of normalized frequency over search grid in the case of color ratio

Once we have the interpolation data as shown in Figures 5 and 7, we implement the Bayesian tracking algorithm on these data. Simulation results for estimating the soot source location using the Bayesian source localization strategy are shown in Figure 8. In this simulation, we use a search grid of 200 m x 200 m grid cells with a threshold of 0.01 for normalized frequency of color ratio measurements and a threshold of 0.007 for normalized frequency of lidar ratio measurements. In other words, we claim existence of soot at certain point in the grid if the normalized frequency of detection from color ratio ≥ 0.01 and the normalized frequency of detection from Lidar ration ≥ 0.007.

Initially, sample points are selected by simply “mowing the lawn” in the cross-wind direction within a bounded search area, the mean wind is from the north. The search pattern for the simulations described here begins at the bottom left. If the concentration does not exceed the threshold values simultaneously, continues to the next grid cell in the lawn mower pattern. If the concentration exceeds the threshold values, the measured concentration is used to update the posterior probability for all cells in the grid and the then directed to the grid cell with the highest probability of containing the source. The map is updated after each detection, and the estimated source location is defined as the point at which posterior probability is maximum.
Figure 8 shows posterior probability distribution at the final detection point. The posterior probability is highest in the region around the estimated source location and nearly zero elsewhere.

The simulation shows that the source of the soot over the grid of study is located near the point of intersection of Hampton Blvd and 49th street. A close observation of traffic pattern for Hampton Blvd suggests that the source of soot at this point may make sense because it is the main traffic light in the area of the campus and the diesel trucks most likely stop by it more than other parts of Hampton Blvd in the area of study.



(a) Posterior

Figure 8. Final probability distribution

6. Conclusion

The study in this report identifies the possible source of the aerosol, in particular the soot, in the vicinity of ODU campus. Lidar is employed to collect data of aerosol profiling in the atmosphere at several sites in the campus. Lidar and color ratios are retrieved from the data as aerosol’s optical parameters. A Bayesian tracking algorithm is employed to track the detection frequency of the soot in the data. The results of the lidar data analysis and tracking show that Hampton Blvd that passes by the campus is a primary source of harmful soot aerosol that is emitted by the diesel trucks in the region.

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