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ATMOSPHERIC AEROSOL SIZE RETRIEVAL FROM LIDAR DATA APPLYING GENETIC ALGORITHM APPROACH.

Sylvain Geffroy[1,2], **Emeric Frejafon**[2] and **Patrick Rairoux**[1]

[1]*LASIM, University Claude-Bernard Lyon 1, 43 bd. 11 Nov., 69622 Villeurbanne Cedex, France.*
geffroy@lasim.univ-lyon1.fr,rairoux@lasim.univ-lyon1.fr
[2]*INERIS, Parc technologique ALATA BP2, 60550 Verneuil-en-Halatte, France. frejafon@ineris.fr*

ABSTRACT

In this paper we present a novel approach using a genetic algorithm (GA) to solve the Lidar "ill-problem". It is inverting aerosol size distribution from multi-wavelengths Lidar data in the UV-VIS-IR spectral range. This method do not need any predefined size distribution shape and its also running with data having poor S/N. Numerical convergence test of the GA have been done on both simulated data and on Lidar field measurements performed during the French POVA [4] Campaign. It shows that size distribution is retrieved in millisecond range, which represent a considerably decreasing in computing time consuming. Comparison between GA size distribution retrieval and SMPS ground-based measurements has been done showing an excellent agreement.

1. METHOD

Retrieving the atmospheric aerosol size distribution remotely is a non-trivial problem where several authors [1,2,3] have made important contributions. The main difficulty for retrieving the atmospheric aerosol size distribution based on remote sensing data is to find the solution of a "ill-posed" problem. In particular, in a single scattering regime, a first kind Fredholm integral expressing the extinction coefficient for a system of particles $\alpha(\lambda,z)$ should be solved. In term of aerosol size distribution the extinction coefficient is given by:

$$\alpha(\lambda,z)=\int \pi r^2 Q_{ext}(r,\lambda,m)n(r,z)dr \quad (1)$$

where $n(r,z)$ is the size distribution (product of $N(z)$ the number of aerosol and $\rho(r,z)$ the normalized size distribution). r is the radius of the particles and z is the distance of the particles from the Lidar position. $Q_{ext}(r,\lambda,m)$ is the extinction efficiency, m the refractive index, λ the wavelength. The relation between the optical extinction and the size distribution can be expressed, as a matrix, where a discretization of the integral should be made using kernel and error function [1,2].

$$K_\lambda^r=\pi r^2 Q_{ext}(r,\lambda,m) \quad (2)$$

where K_λ^r is the extinction Kernel.

$$\begin{bmatrix}\alpha_{355}\\ \alpha_{532}\\ \alpha_{1064}\\ \ldots\end{bmatrix}=N\begin{bmatrix}K_{355}^1 & K_{355}^2 & K_{355}^3 & \ldots\\ K_{532}^1 & K_{532}^2 & K_{532}^3 & \ldots\\ K_{1064}^1 & K_{1064}^2 & K_{1064}^3 & \ldots\\ \ldots & \ldots & \ldots & \ldots\end{bmatrix}\cdot\begin{bmatrix}N_1\\ N_2\\ N_3\\ \ldots\end{bmatrix}+\begin{bmatrix}\varepsilon_1\\ \varepsilon_3\\ \varepsilon_3\\ \ldots\end{bmatrix} \quad (3)$$

Based on predefined kernel function, a genetic algorithm (GA) is applied to solve the matrix system (3), obtaining also a discretized size distribution $\rho_i(z)$ and then the number of particle $N(z)$ using equation (1).

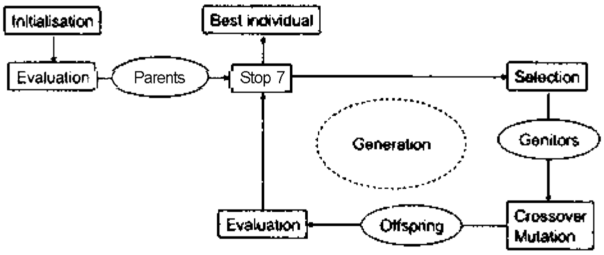

Figure 1: Principle of genetic algorithm.

Genetic algorithms have been widely used [5,6], as they are efficient for solving complex optimization problems. Applying GA for solving our problem, a standard presentation related to live science can be used (show figure 1). The algorithm is based on natural survival mechanisms to the involved quantities by mating, and mutation. These mechanisms are applied to a set of vectors, which represents a population. They correspond to chromosomes in the context of GAs, which are all possible solutions of the problem and are characterised by a specific "fitness", i.e. their performance with respect to objective functions such as chi-squared values. Vectors having low fitness may then enter the mating population to produce an offspring for the next generation, while vectors having high fitness are cancelled. Applying crossover and mutation - operations on these vectors will then create a new population as input for a new iteration. After a given number of generations, an optimal solution is then obtained, which corresponds to the most relevant vectors.

Finally, a GA searches the solution space of a function by using simulated evolution where the fittest individuals reproduce and survive to the next generation, thus improving successive generations. However, inferior individuals also have a chance to survive and reproduce. Through this technique, all regions of the state space are explored. In many situations, particularly when complex optimization problems with numerous local optima should be solved, genetic algorithms provide an effective alternative.

Genetic operators are used to create new solutions based on existing solutions within the population. There are two basic types of operators: crossover and mutation. Crossover takes two individuals and produces a new individual, while mutation alters one individual to produce a new individual.

In our investigation, the initial population is $[\rho_i]$, where vectors are generated randomly from uniform distribution and each variable is chosen within prescribed limits. The number of individuals in the population remains fixed and it is chosen at initialization. The GA then moves from generation to generation until a termination criterion met the optimized fitness. The stopping criterion is a specified maximum fitness (χ^2 test). The process is monitoring by plotting the value of the fitness as the generation progress.

2. RESULTS

To test this retrieval method based on remote sensing measurements, simulated and experimental data were used. Results obtained on numerical data using 355, 532, 1064 and 3370nm as Lidar wavelength are presented in Figures 2 and 3. To approach real measurement condition, random errors have been added on simulated data in order. For the first test of the algorithm (see Fig. 2). A real size distribution measured in urban area (Lyon [7]) has been considered for optical extinction simulation. In figure 3 a tabulated "remote continental" [8] size distribution has been used for optical data simulation. In both case, the GA could retrieve the shape of the distribution with an error on the concentration depending on the S/N of the optical data (10 % relative error on optical data has been considered).

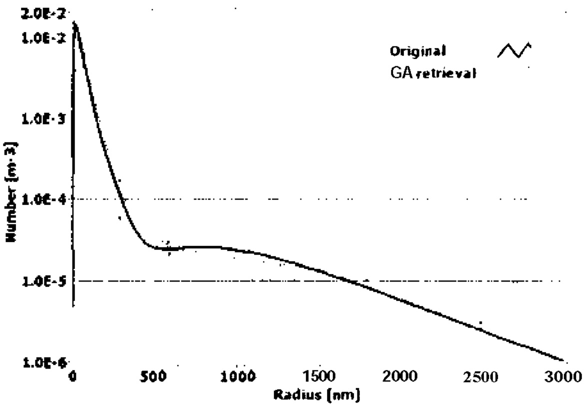

Figure 2: Convergence test of the genetic algorithm (dash) performed on optical extinction data calculated with urban size distribution (line).

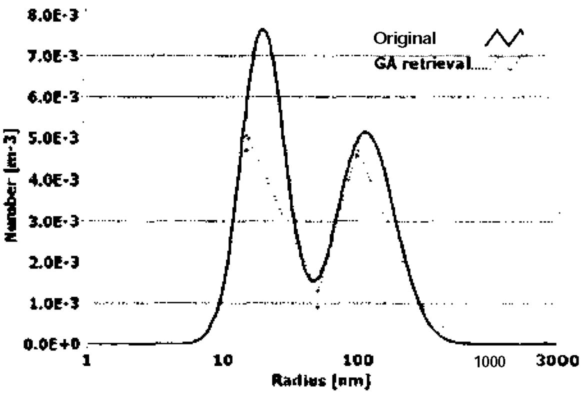

Figure 3: Convergence test of the genetic algorithm (dash) performed on optical extinction data calculated with a tabulated size distribution as remote continental (line).

To validate this novel inversion algorithm, experimental multi-wavelengths Lidar data, performed during POVA field experiment, have been considered. POVA (Pollution en Vallées Alpines) is a research program supported by the French national PRIMEQUAL2 program. Launched in 2000, it was focused on atmospheric chemistry study in the two transit corridors between France and Italy: the Chamonix and Maurienne Valleys. It includes several field campaigns and a very large study realized during summer 2003, associating field measurements with 3D regional scale modelling related to this specific topography.

UV-VIS-IR Lidar measurements were performed with two instruments located at the same position during the field experiment: the INERIS LIDAR, which is a solid state multi-DIAL system (Elight laser system Germany) operating in the UV-VIS spectral range and the CEA/LSCE LIDAR operating in the VIS-IR spectral region (see Figure 5.

Figure 5 : POVA field experiment in Chamonix (summer 2003). The two **mutli-wavelenghts lidar** instruments are shown: on the right the **UV-VIS INERIS** device and on the left the **VIS-IR** CEA/LSCE system.

Hence, measurements at four wavelengths (293, 400, 532 and 1064 nm) have been performed for this purpose. Typical data is shown in figure 5.

The Figure 4 shows a typical Lidar profile measured in the VIS spectral range, showing a strong vertical stratification of the aerosol in the atmosphere and this especially at 500 m above ground level (agl).

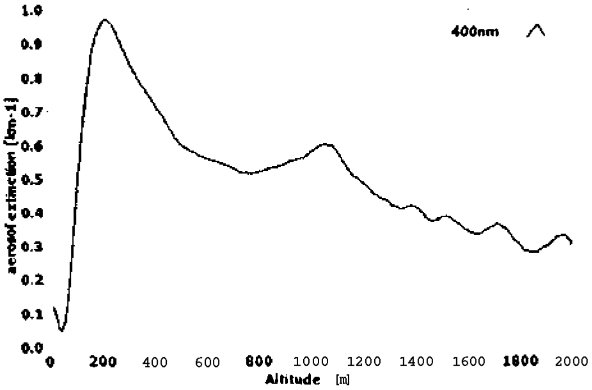

Figure 4: Typical Lidar signal at 400nm during POVA campaign.

The genetic algorithm was applied on extinction profile provided by two multi-wavelengths Lidar at an altitude of 500 m agl. A discretization at 6 different sizes was considered, covering the 20 nm to 2.5 urn size range. Computation of the kernel functions in regard to the 4 wavelengths were made considering spherical and fractal particles. The retrieved size distribution is shown in figure 6. Ground based **SMPS** (Scanning electric Mobility Particle Sizing) is also presented in this figure for validation purpose. The SMPS, which has a sizing range between 15 nm and 700 nm, shows a main mode centred at 100 nm and two other modes at the edges of its operating region. The GA retrieves the 100 nm mode and in the same way, two secondary modes. The mode in the micrometer size range could not be validated by the SPMS due to its size cut-off by 700 nm size.

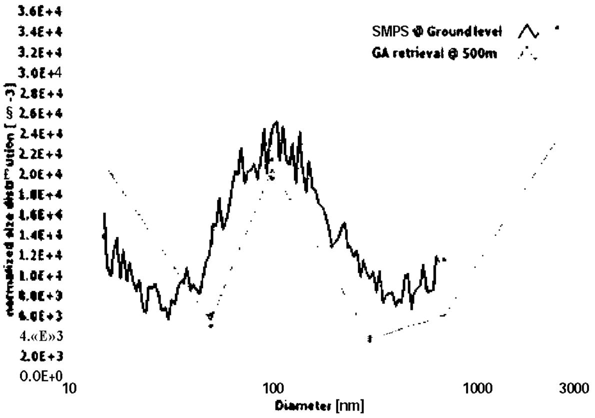

Figure 5: Field experiment results. Chamonix, July 2003. Comparison between SMPS measurements and genetic algorithm output at an altitude of 500m above ground level using multi-wavelengths Lidar measurements performed at 293, 400, 532 and 1064 nm.

3. DISCUSSION AND OUTLOOK

he first results of this novel approach in solving the Ldar "ill-problem" using field measurements are promising in regards to the first validation. Moreover, GA approach bring several advantages in remotely atmospheric aerosol sizing. The first one is the low computation time (less than a second using a desktop computer). Secondly, Lidar signals at least 4 different wavelengths with low S/N (in the 10% range) are necessary to evaluate the main modes of the size distribution.

However, several improvements should be made and this especially on the particle refractive index, which is taken as parameter in the actual GA. In further work, the refractive index retrieving will be included in the GA. The particles radius range of the retrieving procedure will be also investigated to monitor bigger aerosols size. For this, several algorithms, each dedicated to different size range can simultaneously run due to the fast computation time. Further validation of this algorithm will be made on different type of atmospheric aerosols, as for example background aerosols, Sahara dust, haze and clouds. In field measurement, combing 3D scanning multi-wavelengths Lidar and standard ground-based device could rise to a quasi on-line measurement of the spatial and time distribution of the atmospheric particles size.

Passive optical remote sensing measurements of the atmosphere like sunphotometer data will be also explored with this algorithm and also extra-terrestrial aerosols of Mars and Titan.

4. ACKNOWLEDGEMENTS

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