Database of the optical properties of chaotically oriented fractal-like clusters of spherical particles

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1 Introduction

In many fields of science a remote sensing is very often the only way of scattering objects investigation. Commonly it is necessary to determine microphysical properties of scatterers (their size parameters, complex refractive indexes, form etc.) using characteristics of the incident and scattered radiation, which are known from the observations. The solution of this so-called "inverse scattering problem" is conjugated with solving the direct scattering problem, which input parameters are microphysical properties of scatterers whereas output parameters are characteristics of scattered radiation (scattering matrix). Fitting observed results with those obtained from direct problem, some conclusion about scatterer properties can be made.

The complexity of the direct problem depends on such its input parameters as shape, size and composition of the scattering particles. Sometimes to reduce number of these parameters and simplify calculation procedures the model of regular shape particle (spherical, spheroidal particles etc.) is used. However, many scattering particles of natural and artificial origin are aggregates (clusters) of smaller particles (for instance, cometary and interplanetary dust [1]) and their shape seems to be fractal-like. The optical properties of such compound particles appreciably differ from those of isolated particles [2]. Calculation of scattered radiation characteristics for such fractal clusters is a time consuming procedure. Moreover for interpretation of remote sensing results such calculation must be carried out in wide range of the size parameters, complex refractive indexes and parameters, characterizing cluster structure. Therefore for solving inverse scattering problem a detailed database of radiation scattering properties of fractal cluster is needed. To generate such database we use artificial neural network. Properly trained for this purpose artificial neural network allows determining desired data from the range of those were used for training.

2 Model of dust particles

The most powerful and widely used methods for calculations of scattering matrix of fractal cluster are based on the DDA approximation and the theory of light scattering by cluster of spherical particles [2-4]. The last one was used to obtain the massive of data for neural network training.

At present time the procedure of calculation of scattering matrix is well developed both for oriented clusters of spherical particles and for chaotically oriented one [4]. But the observed dependencies of scattered light polarization by cometary and interplanetary dust, in particular, orientation of plane of polarization with respect to the scattering plane, allows one to expect that dust particles are chaotically oriented. More over to reduce number of input parameters the cluster constituent spheres are usually chosen identical to each other. Thus for model of chaotically oriented cluster of identical spherical particles the direct scattering problem have such input parameters: the wave parameter of constituent spheres $x = 2\pi a\lambda$(a is sphere radius, λ is the wavelength of incident radiation), real and imaginary part of complex refractive index m, number of particles in the cluster (N) and the parameters describing the cluster structure. Structure of fractal-like cluster consisting of a great number of particles can be characterized by two parameters only [5]. These are fractal dimension D and a prefactor constant ρ.

3 The multi-layered perceptron

One of the widely used models of neural network is the multi-layered perceptron [6]. The network has layers of input and output elements called neurons. Several "hidden" layers can be located between these layers. Each neuron in a layer is connected to the neurons in the adjacent layer with a modifiable connection, there are no connections between neurons of the same layer. An input vector is put on the input layer, pass through the hidden layers, and arrives at the output layer. Corresponding output vector is determined by calculation of neuron activity level for each layer using already known values of neuron activity of the previous layers.

For perceptron training the algorithm of back error propagation is used, which consist in the following. Small random values are assigned to connections before the start of training. Training is an iterative process. Each of iterations consists of two phases. An input vector is putted to the network during the first phase (input elements are set in the proper condition). Then the signal passes through the network and generates an output vector. Received output vector is compared to the required one. If they coincide, training of the perceptron for this input vector is not carried out. In the other case, difference between the actual and required output values is calculated and sent consecutively from the output layer to the input one. According to this information, modification of connections is being fulfilled using the generalized delta-rule [6]. Weight modification is applied for each input-output pair. Training is being continued until the error decrease to the given value.

Perceptron is trained on the limited set of the input-output parameters. In the process of training it builds a surface in the space of these parameters and defines memorized a continuous function, associating the input and output parameters.

4 Database of optical cluster properties on the basis of the perceptron

Perceptron structure, on the basis of which the database is build, is defined by number of input and output parameters and a required accuracy. The number of input neurons corresponds to the number of parameters defining of the cluster properties: $x, Re(m), Im(m), D, \rho, N$. The output perceptron data are the expansion coefficients of the scattering matrix elements in series of the generalized spherical functions. The data for perceptron training was obtained using D. Mackowsky and M. Mishchenko code [4] [3]. At $N = 50$ the number of nonzero coefficients is approximately 22-24. So, the number of output neurons is 30, and the number of "hidden" layers is 2 with 30 neurons in each layer.

Generation algorithm for fractal-like cluster of particles can be defined by the following formulas:

$$N = \rho \left(\frac{R_g}{2a} \right)^D, \tag{1}$$

where R_g is the gyration radius of the cluster

$$R_g^2 = \frac{1}{N} \sum_i^N r_i^2, \tag{2}$$

r_i is the distance from particle i to the center of mass of the cluster.

Typical cluster structures with the same D, ρ and N but under different initial generation conditions, are given in Figure 1.

About two hundred points for the input parameters in range of $x = 1.5$; $1.4 \leq Re(m) \leq 1.7$; $0.001 \leq Im(m) \leq 0.1$; $D = 3$; $\rho = 8$; $N \leq 50$ was used for training the perceptron. During training process the perceptron is defining and memorizing a hypersurface in space of input-output parameters that in the best way corresponds to the data set presented for training. The trained

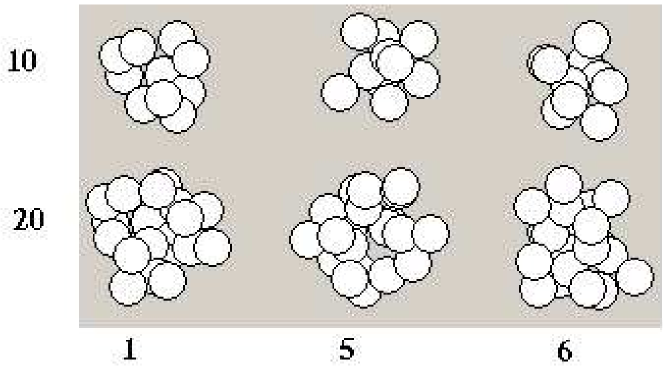

Figure 1: Cluster form for 10 and 20 particles.

perceptron allows calculating the approximate values of the expansion coefficients for any input data from the data range that was used for neural network training.

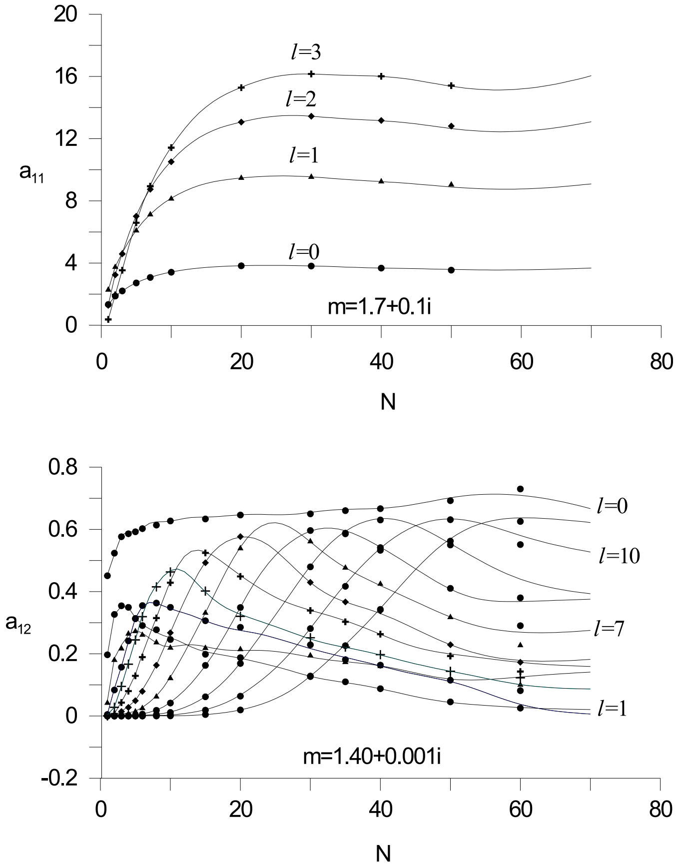

Figure 2: Dependency of a_{11} and a_{12} coefficients on N. L is coefficient number.

Some examples of calculation of the dependencies of expansion coefficients a_{11} and a_{12} of scattering matrixes elements S_{11} and S_{12} are given in Figure 2. Spots are the data obtained directly from the theory of light scattering by cluster of spherical particles. Solid curves correspond to data, calculating by the perceptron.

In Fig.3 the linear polarization degrees of scattered light by clusters are given. Note, that the data for such refractive index ($Re(m) = 1.7$; $Im(m) = 0.08$) were not used for perceptron training.

Advantages of the database are the small size and quick data access. Moreover there is a

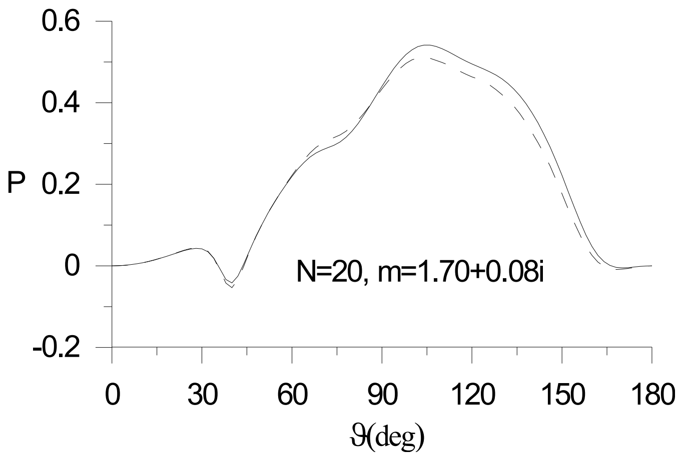

Figure 3: Linear polarization degree P vs scattering angle ϑ. Solid curve corresponds to the accurate values, dotted line corresponds to values calculated by the perceptron.

possibility to extend and make the database more exact without an increasing data time access and size of the database.

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