GApaper

Retrieval of dry snow parameters from radiometric data using a Dense Medium model and Genetic Algorithms

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Abstract.

In this paper, GA-based techniques are used to invert the equations of an electromagnetic model based on Dense Medium Radiative Transfer Theory (DMRT) under the Quasi Crystalline Approximation with Coherent Potential to retrieve snow depth, mean grain size and fractional volume from microwave brightness temperatures.

The technique is initially tested on both noisy and not-noisy simulated data. During this phase, different configurations of genetic algorithm parameters are considered to quantify how their change can affect the algorithm performance. A configuration of GA parameters is then selected and the algorithm is applied to experimental data acquired during the NASA Cold Land Process Experiment. Snow parameters retrieved with the GA-DMRT technique are then compared with snow parameters measured on field.

Keywords: microwave remote sensing, genetic algorithms, DMRT, snow

1. INTRODUCTION

In inverse problems the main task is the determination of a *cause* from its *effects*. In the case of microwave remote sensing, the inversion process can be interpreted as that procedure leading to the extraction of the sought parameters by inverting the relationships relating them to the electromagnetic measured quantities. In general, the retrieval of unknown parameters can be either a well- or an ill-posed problem. The former is defined as a problem that is uniquely solvable and is such that the solution depends in a continuous way on the data. The latter is characterized by the fact that a solution may not exist and, if it does exist, there may be more than one (with a small change in the problem leading to a big change in the solution). If the solution depends in a discontinuous way on the data then small errors, whether rounding off errors, measurement errors, or perturbations caused by noise, can create large deviations on the final solution. An ill-posed problem is not solvable in a strictly mathematical setting and numerical techniques are required.

In the literature, several authors investigated the inversion of the relationships relating the snow geophysical parameters geophysical parameters to the observed microwave radiometric quantities. Techniques based on experimental data and linear regressions (e.g., [**1**-[**3**]) offer the possibility of fast inversions but they are limited by the subset of data used to generate the coefficients in the adopted formulas. Semi-empirical models can also be used by merging theoretical models with experimental data [**4**[**5**] and snow parameters can be retrieved inverting the model either numerically or theoretically. In the last case, the convergence of the solution can be in this case driven by constraints given by ground data and/or by considerations regarding the observed scene (i.e. possible values). The inversion of theoretical models is not always performable by using analytical techniques because of the difficulties of inverting non-linear integro-differential equations (e.g., radiative transfer equations). Thus, numerical approaches such as iterative techniques or artificial neural network based techniques have been proposed in literature [**6**[**7**]. In the case of iterative techniques, such as in example in the case of the Nelder-Mead simplex method **[8**], the convergence of the algorithm to the correct solution is not guaranteed as it depends on the initial conditions. ANN techniques are based on the training of the network by means of simulated or measured data and have shown good performances [**6**[**7**].

In this paper, we propose a preliminary study for the use of genetic algorithms (GA's) to retrieve dry snow parameters from multi-frequency (19 and 37 GHz), multi-polarizations (vertical and horizontal) and multi-angle (observation angle ranging from 30° to 60 °) microwave radiometric data. In future, the use of a single observation angle will be investigated. The GA's are used to invert the equations of an electromagnetic model based on the Dense Medium Theory under the Quasi-Crystalline approximation with Coherent Potential (DMRT). The DMRT model is adopted because it represents a valid tool for simulating snow brightness temperatures, where the assumption of independent scattering is no longer valid [**9**] and scattering among correlated particles must be considered.

The GA's are numerical iterative procedures where a population of individuals is described by a finite string of symbols (*genome*) and encodes a possible solution in a given problem space. The latter is named the *search space* and comprises all possible solutions to the problem. The solution is reached by an iterative procedure and genetically-inspired operators (i.e. *crossover* between two *parents* and *mutation*). The initial guess is not a single set, as it happens in the majority of numerical techniques, but it is made of the entire initial population, whose size is an user-defined option. This is an important factor when dealing with ill-posed problems because it avoids premature convergence of the algorithm. Moreover, genetic algorithm operators such as *mutation* or *crossover* also allow preventing premature convergence to local minima in the solution space, by creating heterogeneity in the search space. The GA software used in this study is a modified version of the Genetic Algorithm Optimization Toolbox (GAOT) for Matlab 5 by Houck et al. [**10**]. The GA algorithm is applied to both simulated and measured brightness temperatures. Results obtained with simulated brightness temperatures are also used to select an optimal configuration of the GA parameters that, in turn, are applied to experimental brightness temperatures. Data used in this study were collected during the NASA Cold Land Processes Experiment (CLPX) performed in Colorado during the third Intensive Observation Period (IOP3) on February 2003 [11-[**13**].

The paper is divided as follows: in the Section I the Genetic Algorithms (GA's) based technique and the electromagnetic model are presented. The successive Section II is dedicated to the GA's and snow parameters. Section III is devoted to the presentation of results and discussion. Finally, Section IV reports conclusions and future works.

2. GENETIC ALGORITHMS (GA's) AND THE ELECTROMAGNETIC MODEL

In this section an overview on the genetic algorithms is given. Then, the basic equations of the DMRT QCA-CP based electromagnetic model used in this study are reported together with a sensitivity analysis.

Genetic algorithms

Genetic algorithms are iterative procedures in which a population of individuals encode a possible solution to a given problem. They are based on Darwin's theory of evolution where problems are solved by an evolutionary process resulting in a best solution (*survivor*). Evolutionary computing was introduced in the 1960s by Rechenberg in [**14**[**16**]. From Rechenberg's work, John Holland invented and developed genetic algorithms, whose basic concepts and mathematical foundation (the *schemata theorem*) are reported in [**17**], which relates the observed fitness of the members of a *schema* (e.g., a set of chromosomes that share certain values) at generation t to the expected number of schema members in the population at the generation $t+1$. Since then, GA's have been widely used for different applications across a large range of disciplines. Every additional application gave a new perspective to the theory so that also the generality, robustness and applicability of genetic algorithms were improved.

The GA begins with an initial population of individuals that are decoded and evaluated according to a fitness function that numerically encodes the performance of each individual. Then, some individuals are selected to continue in the algorithm to the successive iteration. It is evident that selection procedure alone cannot generate new individuals into the population, meaning that it is not possible to find solutions different from those ones generated in the initial population. It is therefore necessary to introduce new operators called the *crossover* and *mutation* operators. The former is applied to two selected individuals (*parents*), by exchanging parts of their genomes to form two new individuals (*offspring).* The crossover operator is controlled by the probability that chromosomes are recombined. This is a user defined parameter, usually set to a high value (e.g. in our case, 95 %). The probability that a mutation occurs is another user-controlled option and it is usually set to a low value (e.g., 5 % in our study) so that good chromosomes are not destroyed. A mutation simply changes the value for a particular gene. In Figure 1, an example of the generation of a new population in a step of the GA procedure is reported. Suppose that the solution is an integer between 0 and 255 and a random 8 bit binary vector is used to represent possible solutions. Among selected solutions, two of them are selected to perform crossover and another is selected for mutation. New individuals are then evaluated through the selection process. The termination condition may be specified as some fixed, maximal number of generations or as the attainment of an acceptable fitness level. As a reference, Figure 2 shows a simplified flux diagram for GA's.

The electromagnetic model and sensitivity analysis

An electromagnetic model based on Dense Medium Radiative Transfer Theory (DMRT) under the Quasi Crystalline Approximation with Coherent Potential (QCA-CP) [10[9[18] is used to invert brightness temperatures to retrieve the dry snow parameters. It is important to recognize that a dense-media based model is fundamental to describe propagation and scattering in dry snow, where the assumption of independent scattering is not valid and dependent scattering must be considered. In the model, the effective propagation constant and albedo are computed under the Percus-Yevick (P-Y) approximation and dry snow-pack is modeled as a slab of densely distributed spherical particles with radius a and permittivity ε_i, embedded in a background medium of permittivity ε_b and lying above the soil (having permittivity ε_g). The expressions for effective propagation constant K and albedo ω can be found in [18]. The DMRT equations assume the same form as the Classical Radiative Transfer equations and can be solved by using Gaussian quadrature and eigen-values and eigen-vectors analysis. The unknown coefficients deriving from eigen-vector analysis can be calculated by means of boundary conditions.

In order, to perform the retrieval of the unknown parameters, it is important that the radiometric involved quantities are sensitive to snow parameters. Investigations have been conducted about sensitivity analysis and they can be found in literature (i.e.[**6**[**9**[**20**]). A sensitivity analysis involving two parameters is conducted using the DMRT model in this study. A strong sensitivity is shown by the 37 GHz channel to the mean particle size with the sensitivity decreasing as the frequency decreases. Brightness temperatures show less sensitivity to the fractional volume than to mean particle size, at both frequencies. Finally, the parameter showing the weakest sensitivity is the snow depth, meaning that large changes in the snow depth may only result in relatively small variations of brightness temperatures. As an example, Figure 3 shows brightness temperatures at vertical polarization as a function of grain size (radius) and fractional volume at 19 (left) and 37 (right) GHz.

3. PARAMETERS IN GENETIC ALGORITHM AND IN SNOW

In this section, the results of a sensitivity analysis of the inputs to the GA are reported. The range in which the snow parameters are allowed to range is also discussed.

GA parameters

The use of GA fundamentally requires the choice of six parameters: chromosomes representation, selection function, genetic operators and reproduction function, initial population, termination criterion and the evaluation function. In this section, we study the influence of the choice of the initial population, termination criterion on final results is studied. In particular, the effects of the choice of the initial population size, of the convergence error of the algorithm and of the number of initial iterations are studied. In order, to this aim the GA is applied to the same set of simulated brightness temperatures several times changing only the population size, the number of initial iterations and the error convergence. The chromosome representation, selection function, genetic operators, reproduction and evaluation functions are kept fixed during the testing.

Fixed GA parameters

The chromosome representation is used to describe the each individual in the population of interest. The alphabets used to describe each individual could consist of binary digits, floating point numbers, integers, symbols etc. etc.. In this study, the representation of an individual involve genes from an alphabet of floating point numbers with values within the variables upper and lower bounds. The choice of the representation for the individuals influence also the choice of the genetic operators. Different crossover operators can be used in the case of the representation of individuals using a floating point alphabet (e.g., simple crossover, arithmetic crossover and heuristic crossover). In this study, we used the arithmetic crossover, which takes two parents (P1 and P2) and performs an interpolation along the line formed by the two parents. If $\underline{X}$ and $\underline{Y}$ are the two parents then two offsprings are produced by the arithmetic crossover as appears in Eq. 1, being r a uniform random number between 0 and 1. The multi non-uniform operator was used for the mutation where all parameters of the parent are changed on the base of a on a non-uniform probability distribution [10]. The non-uniform mutation randomly selects one variable and sets it equal to a non-uniform random number as follows (Eq. 2), where a_i and b_i are, respectively, the lower and upper bound, r_1 and r_2 are two uniform random numbers between 0 and 1 and $f(G) = \left(r_2 \left(1 - \frac{G}{G_{max}} \right) \right)^b$ with G representing the current generation, G_{max} the maximum number of generations and b a shape parameter.

$$\begin{aligned} \underline{X}' &= r\underline{X} + (1-r)\underline{Y} \\ \underline{Y}' &= (1-r)\underline{X} + r\underline{Y} \end{aligned} \qquad \text{Eq. 1}$$

$$x' = \begin{cases} x + (b_i - x) f(G) \rightarrow r1 < 0.5 \\ x + (x + a_i) f(G) \rightarrow r1 \geq 0.5 \\ x \rightarrow otherwise \end{cases} \qquad \text{Eq. 2}$$

Let us report a numerical example in the case of the inversion of one single snow parameter, such as mean grain size. Let the lower and upper bound be $a_i = 0.1\text{mm}$ and b_i = 2 mm, the maxim number of generations G_{max}= 500, the current generation G = 100, the shape parameter b = 0.3, $r1 = r$ = 0.234 and $r2$=0.675 and $\underline{X}$ = 0.345 mm and

$\underline{Y}$ = 0.678 mm. The results of the crossover operator are $\underline{X}$' = 0.600 mm and $\underline{Y}$'= 0.422 mm. The performances of the offspring are evaluated through the evaluation function and compared with those of the parents. Among the four (parents and offspring), the two individuals showing the best performances are selected for the next generation. In the case of the mutation operator we have $f(G)=f(100)$=0.831, $r1 < 0.5$ implying x'= 0.345+(2-0.345)*0.831=1.72 mm. Note that the effects of the mutation operator on the individual decrease as the number of generations increase (e.g., for G = 400, $f(G)$= 0.548 and for $G=G_{max}$ $f(G)$=0).

Several selection methods exist in literature such as tournament selection, roulette wheel and ranking methods [**10**]. In this study, the tournament selection method is used, in which each chromosome in the population competes for a position in the mating subset. The selection works as follows: two chromosomes are drawn at random from the population and the chromosome with the highest fitness score is placed in the mating subset; then, both chromosomes are returned to the population and another tournament begins. This procedure continues until the mating subset is full. A main characteristic of this scheme is that the worst chromosome in the population will never be selected for inclusion in the mating subset. Finally, the evaluation function is represented by the difference between the target brightness temperatures and those obtained with the elements of the population.

Variable GA parameters

The population size dictates the number of chromosomes in the population. Larger population sizes increase the amount of variation present in the initial population at the expense of computational time. Three values of the population initial size having, respectively, 15 (5*N, with N=3 being the number of parameters to be retrieved), 30

(10*N) and 60 (20*N) individuals are considered. Generally, a large population size is preferred to maintain diversity among the individuals and hence better exploration of the solution space. An alternative to the use of a high number of individuals in the initial population is to keep high mutation rates and uniform crossover. However this case is not examined in this paper and the probabilities of crossover and mutation are fixed, respectively, at 0.95 and 0.1. The shape factor for non-uniform mutation is fixed to 3 [**10**].

The effect of changing the convergence error value on the GA performance is also analysed. The algorithm stops either when the Root Mean Square Error (RMSE) between brightness temperatures retrieved by the GA algorithm and those to be inverted ("target brightness temperatures") reaches a fixed value or when a maximum number of iterations is performed. Two values of error are considered: 0.1 and 10 K. The maximum number of iterations is fixed at 50 because of past-performed analysis on snow retrieval techniques based on GA [**20**].

The number of initial iterations, being the number of iterations performed on the initial population, is also another parameter considered for the sensitivity analysis. In the cases here studied, this parameter could be 10 or 50 iterations.

The maximum number of chromosomes in the tournament selection method is set to 10 and it is fixed for all examined cases. This choice is based on other studies conducted in [**20**].

Snow parameters

The ranges of values in which snow parameters are allowed to range are the following: snow depth 0.1-1.5 m, particle size (diameter) 0.1 - 3 mm, fractional volume 0.1-0.4 (corresponding to a density ranging between 90 and 370 Kg/m^3). The remaining input parameters to the electromagnetic model are kept fixed as follows: snow temperature T_{snow} = 269 K, ground temperature T_{ground} = 273 K, ground permittivity ε_{ground}= 4.5 + i0.1. These values are the same as those used in the simulations to generate the simulated target temperatures. In addition, they are very close to the values obtained from field measurements for those cases when the technique is applied to experimental brightness temperatures [**13**[**19**]. The effects of roughness at the air/snow and snow/soil interfaces are neglected for simplicity, but will be considered in future studies.

4. RESULTS AND DISCUSSION

As GA are stochastic procedures, for each set of unknown parameters to be retrieved the solution is obtained by running the algorithm 50 times. The 50 results are then used to extract the mean value and standard deviation of the retrieved snow parameter.

Table 1 summarizes the different combinations of GA parameters analyzed. In the cases from A to D, the technique is applied to not-noisy simulated brightness temperatures. In the cases from D2 to F, a random error with ±5 K range is added to the simulated brightness temperatures. The results obtained for cases without added error (from A to D) are shown in Table 2. The snow parameters used to generate the simulated brightness temperatures (and hence to be retrieved) are diameter $D=2a = 1\ mm$, fractional volume $f = 0.3$ and snow depth $d = 0.8\ m$. In Table 2, two results are reported for each parameter: the case named *'initial selection'* refers to the value obtained by using only the initial iterations. The results reported in Table 2 shows that the parameter retrieved with the lowest error (between 1.2 and 3.6 %) and standard deviations is the mean grain size. The values of fractional volume are retrieved with an error between 11% and 16 %. The values of snow depth are retrieved with an error between 8.8 % and 27.5 %. The results also show that the choice of GA parameters does not strongly affect the retrieval of mean particle size or fractional volume. The retrieval of snow depth , however, does improve as the size of the initial population increases (cases C and D), mainly because of the increase in the diversity of the initial population. We also note that no significant difference occurs with regard to snow depth retrieval when a large number of initial iterations is used and the number of elements in the initial population is the same (cases A and B).

The results obtained when random noise (±5K) is added to the simulated brightness temperatures are reported in Table 3. References value for snow parameters are the same as those used previously (mean particle size diameter $D = 2a = 1\ mm$, fractional volume f

= *0.3* and snow depth *d =0.8 m*). In the Table, the results obtained with the configurations denoted with letters F and D2, a variant of the case D (see Table 1), are reported. The case denoted with D2 was not initially considered but it was suggested by the encouraging results obtained with the case D. Also, in this case the mean particle size shows a weak sensitivity to GA parameter variations. The performances of fractional volume and snow depth retrievals improve by about 10 % when the algorithm convergence value (RMSE) is decreased from 10 to 0.1 K. Table 4 and Table 5 show the results obtained with the technique applied to different sets of snow parameters, using the F and D2 configurations. The D2 configuration gives better results than the F configuration, but both cases fail in the case # 2. Low values of snow depth may be the reason for the errors.

Application of the GA to measured brightness temperatures

The D2 configuration was used to extract snow parameters from measured brightness temperatures. The microwave radiometric data used in this study were collected by the University of Tokyo's ground based passive microwave radiometer (GBMR-7) during the NASA Cold Land Process Experiment (CLPX-1) in February 2003 [**11**]. During the experiment, measurements of snow properties (e.g. snow depth, density, temperature and mean particle size) were performed at least daily [**21**]. Snow parameters collected in the field were averaged along the vertical profile of the snowpack and compared with those retrieved using the GA-based technique applied to the GBMR-7 data. Figure 4 and Figure 5 show, respectively, the results obtained for fractional volume and snow depth. Figure 4 shows the comparison between average values of measured fractional volume (black circles) vs. retrieved fractional volume (white squares). For all dates, the retrieved values of fractional volume are in good agreement with those ones measured on the field, with a maximum absolute error of 0.02 (relative percentage error less than 10 %).

Figure 5 compares the retrieved and measured snow depths. For values of snow depth lower than 0.8 m (first three days of the IOP3), the results obtained with the GA are in good agreement with the experimental data (maximum percentage error 12.6 %). The error between measured and retrieved values of snow depth increases (reaching a peak of about 40 %), as snow depth increases. This suggests that a threshold exists around 0.7-0.8 m of snow depth above which the GA depth retrieval fails. These results are consistent with those reported in literature (i.e. [2[4[7]) where a threshold exist for the retrieval of snow water equivalent and snow depth. The average threshold value for is around 150 mm SWE and for snow around 60-80 cm. During the observation period, high values of snow depth were present beginning February 21, corresponding to SWE values between 155 and 250 mm, when the retrieval of snow depth fails. Another factor was the occurrence of new snow events during the period of observation. This fresh snow was characterized by small particles (0.05 mm) and very low density (lower than or comparable to 90 kg/m^3). As a consequence, the measured height of the snowpack increased but the effect on the recorded microwave radiation was very small, due to the low sensitivity of the 19 and 37 GHz brightness temperatures to this type of snow. Stratification effects, not considered by the electromagnetic model, may also influence the performance.

The comparison between GA-retrieved mean particle size (diameters) and the average values of ice crystals size is reported in Table 6. In general, the values retrieved with the GA are in good agreement with the averages of measured values. The values retrieved by means of the DMRT model (through the GA) represent the mode of a probability density function describing the particle sizes distribution where reference values of measured particles are obtained averaging measurements carried out on particles with different shapes. The values retrieved by the GA algorithm are in good agreement with the mean of the distribution of snow grain sizes reported in literature by Nakamura [23] where the distribution of snow particles in different types of artificially produced snow was computed by counting the number of particles in different size ranges. The distribution obtained is similar to a log-normal distribution. The values of mean particle size retrieved by the inversion of the DMRT model correspond approximately to the mean of the grain size distribution for metamorphosed snow - the type of snow observed at the CLPX-1 test site.

5 CONCLUSIONS AND FUTURE WORK

A technique based on genetic algorithms and Dense Medium Theory is proposed for the retrieval of dry snow parameters (fractional volume, snow depth and mean particle size) from microwave brightness temperatures (19 and 37 GHz). The technique is applied to both simulated and measured brightness temperatures.

The results obtained in the case of simulated brightness temperatures show that the technique is able to retrieve the snow parameters very satisfactorily. For both cases of noisy and noise-free simulated brightness temperatures, good results are achieved for all seven considered configurations of GA parameters. In general, the snow parameter retrieved with the lowest error is mean particle size. The retrieval of fractional volume is performed with an error higher than for mean grain size but lower than for snow depth. The inversion of noisy simulated brightness temperatures has also demonstrated that the number of elements in the initial population becomes an important factor for the retrieval of snow depth.

The inversion algorithm has been applied to the brightness temperatures collected during the IOP3 period (19-25 February 2003) of the NASA Cold Land Process Experiment. The retrieval of mean particle size and snow fractional volume shows good results, for all considered dates, with maximum relative percentage errors of 10-12 %. In the case of snow depth, for high values of snow depth the performance of the algorithm deteriorates, reaching a relative percentage error of 40 %. The existence of a threshold value for the snow depth retrieval that is related to the microwave penetration depth at 19 and 37 GHz and the presence of new fresh snow are among the reasons for the deterioration of algorithm performance.

In the future, the algorithm will be tested using single-angle multi-frequency/polarization radiometric data and the number of parameters to be retrieved will be increased to consider roughness at snow/soil interfaces, snow wetness and other parameters related to the DMRT (i.e. such as *stickiness* [24]). In the form presented in this paper, the algorithm will be tested on other data acquired during the NASA CLPX-1 period in dry and wet snow conditions as well as on other existing literature data.

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FIGURES

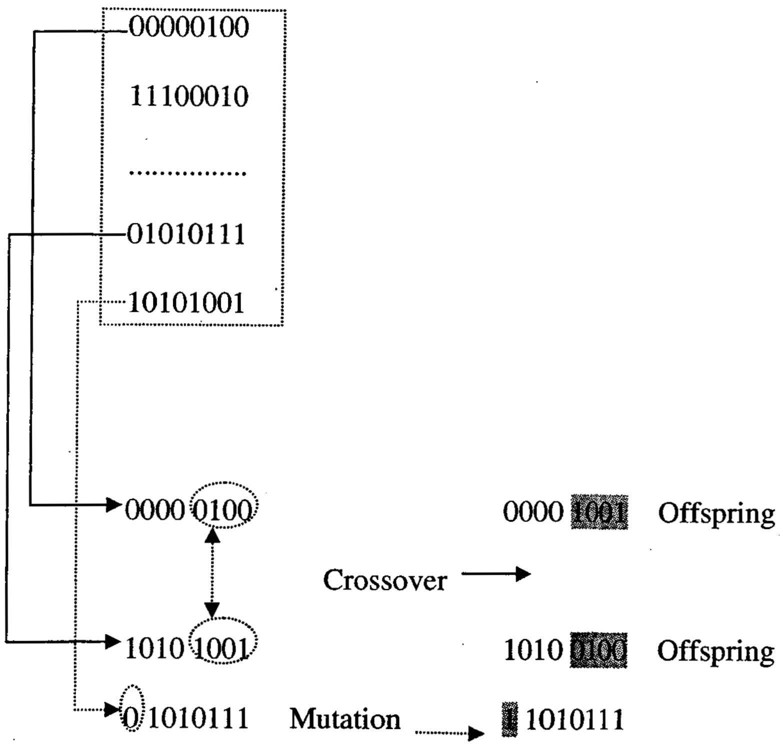


Figure 1 Example of the mutation and crossover operators

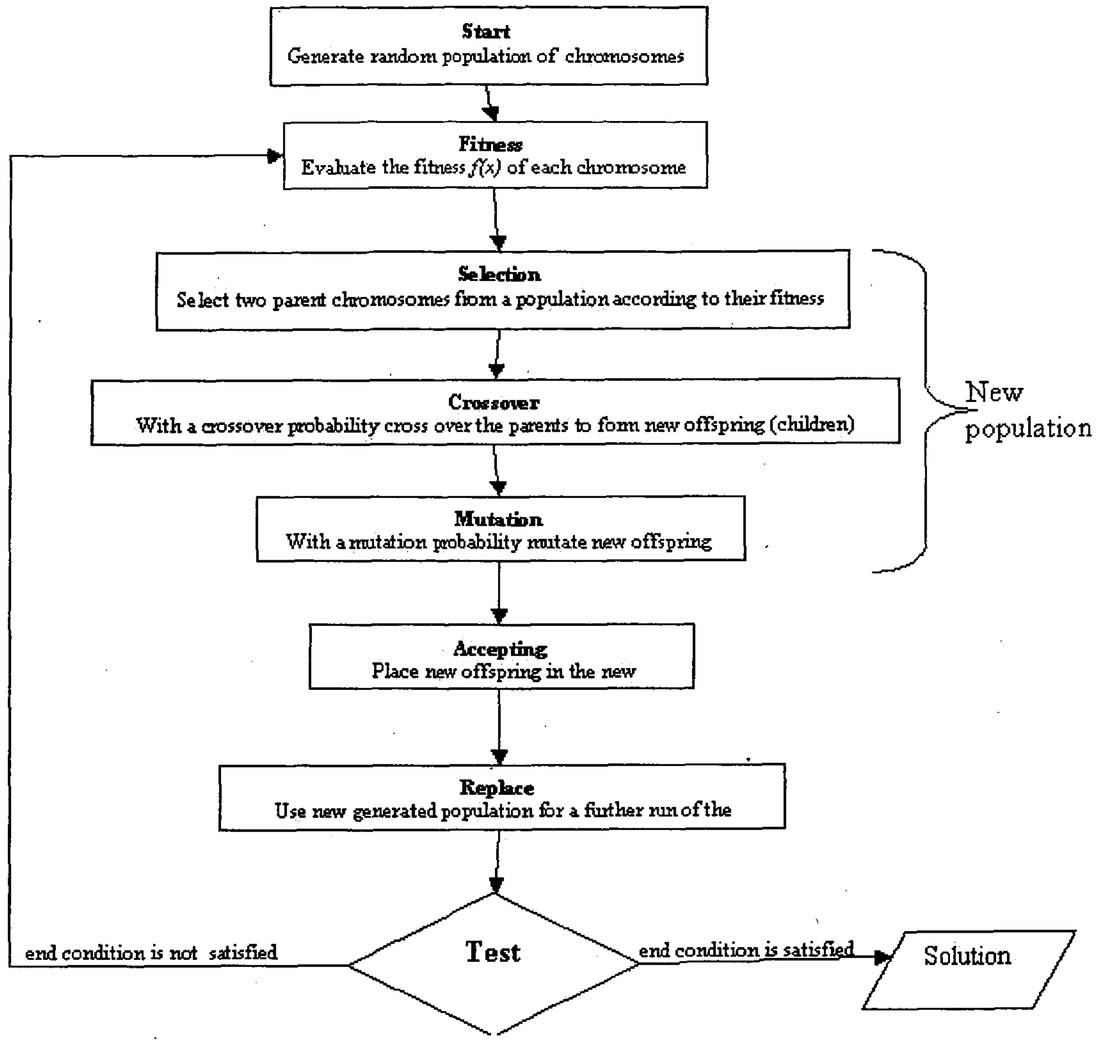
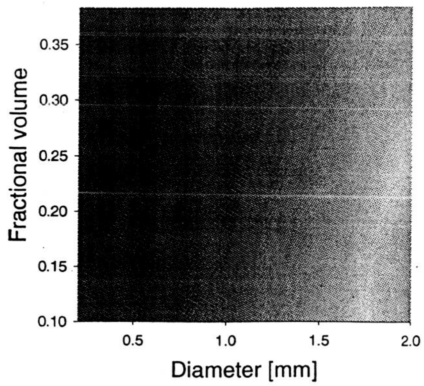
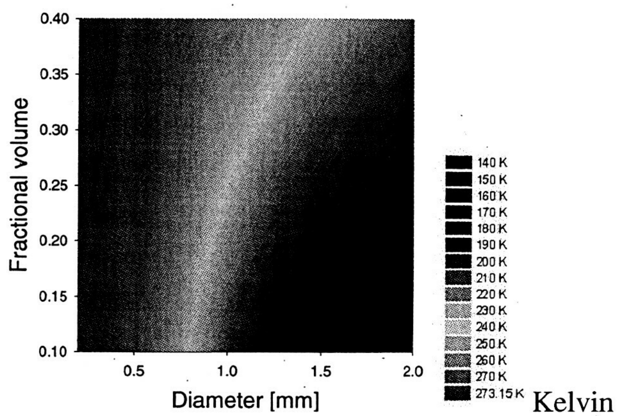


Figure 2 Flux diagram for the GA



(a)



(b)

Figure 3 Sensitivity analysis of the electromagnetic model: brightness temperature (V. pol) as a function of grain size (radius) and fractional volume at 19 (a) and 37 (b) GHz

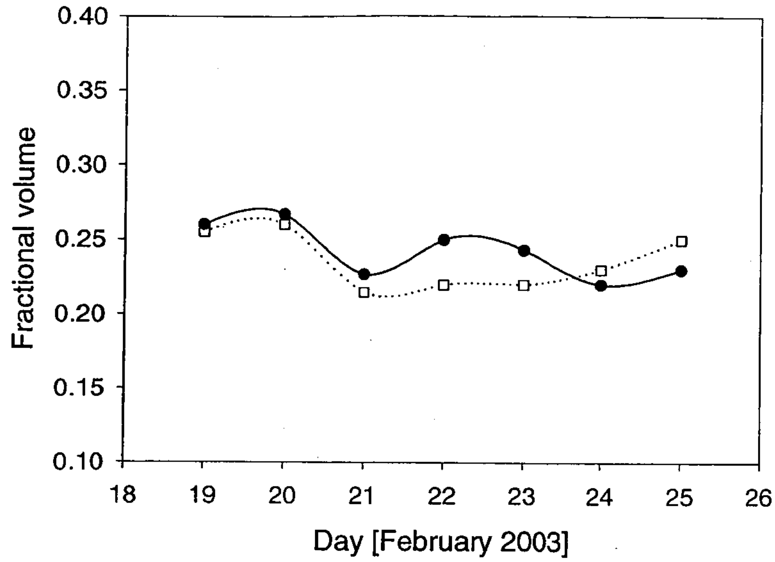


Figure 4 Measured (squares) and retrieved (circles) fractional volume for the different dates of the CLPX-1 IOP3 period

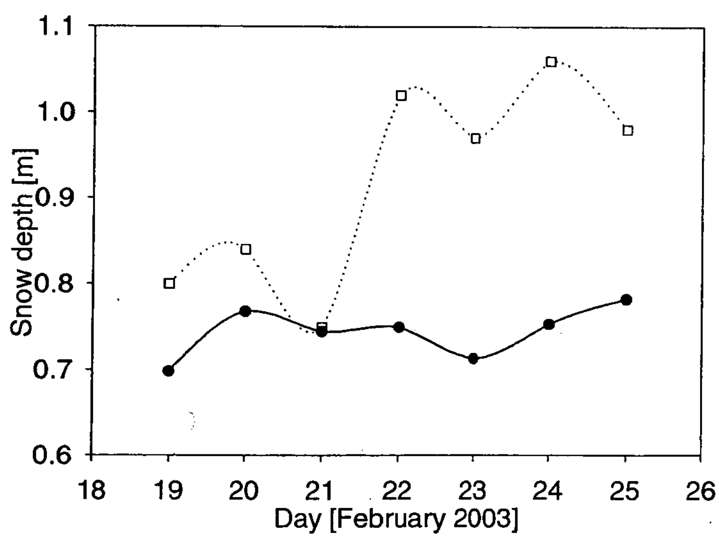


Figure 5 Measured (squares) and retrieved (circles) snow depth for the different dates of the CLPX-1 IOP3 period

TABLES

	A	B	C	D	D2	E	F
Population size	15	15	30	60	60	15	15
Init. iteration	10	50	10	10	10	10	10
Convergence it.	50	50	50	50	50	50	50
Conv. Error [K]	0.1	0.1	0.1	0.1	10	0.1	10
Added Random error [K]	0	0	0	0	±5	±5	±5

Table 1 Test configurations for the Genetic Algorithm-based technique

	A		B		C		D	
	Mean	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Radius [mm]								
Initial selection	0.511	0.1	0.512	0.107	0.493	0.08	0.493	0.08
Convergence value	0.506	0.07	0.487	0.069	0.482	0.06	0.491	0.08
Fractional volume								
Initial selection	0.261	0.09	0.242	0.09	0.247	0.08	0.266	0.08
Convergence value	0.257	0.08	0.253	0.06	0.252	0.07	0.267	0.08
Depth [m]								
Initial selection	0.553	0.24	0.565	0.288	0.664	0.231	0.724	0.213
Convergence value	0.58	0.23	0.645	0.211	0.68	0.190	0.721	0.199

Table 2 Results for different GA configuration parameters in the case of brightness temperatures without noise. Expected values are: $a = 0.5$ *mm*, $f = 0.3$ and $d = 0.8$ *m.*

Radius [mm]	E		F	
	Mean	**Std. dev**	**Mean**	**Std. dev**
Initial selection	0.511	0.102	0.509	0.09
Convergence value	0.515	0.094	0.511	0.09
Fractional volume				
Initial selection	0.264	0.09	0.251	0.09
Convergence value	0.27	0.08	0.257	0.08
Depth [m]				
Initial selection	0.636	0.243	0.566	0.267
Convergence value	0.63	0.238	0.593	0.263

Table 3 Results for different GA configuration parameters in the case of noisy brightness temperatures. Expected values are: $a = 0.5\ mm$, $f = 0.3$ and $d = 0.8\ m$.

	Case F	Depth [m]	Fractional volume	Radius [mm]
	Depth[m], Fractional volume, Radius [mm]			
1	0.8 0.35,0.3	0.503±0.237	0.242±0.08	0.644±0.09
2	0.2,0.2,0.5	0.566±0.244	0.242±0.07	0.222±0.06
3	0.6,0.3,0.6	0.534±0.254	0.27±0.09	0.616±0.11
4	0.5,0.3,0.8	0.64±0.267	0.257±0.09	0.51±0.09
5	0.8,0.38,0.8	0.53±0.272	0.281±0.09	0.745±0.11

Table 4 Results of GA algorithm for different combinations of snow parameters using configuration F

	Case D2	Depth [m]	Fractional volume	Radius [mm]
	Depth[m], Fractional volume, Radius [mm]			
1	0.8,0.35,0.3	0.65±0.17	0.29±0.06	0.24±0.06
2	0.2,0.2,0.5	0.581±0.22	0.22±0.07	0.21±0.05
3	0.6,0.3,0.6	0.593±0.23	0.26±0.09	0.59±0.09
4	0.5,0.3,0.8	0.547±0.25	0.26±0.08	0.63±0.08
5	0.8,0.38,0.8	0.49±0.22	0.29±0.08	0.75±0.1

Table 5 Results of GA algorithm for different combinations of snow parameters using configuration D2

	Retrieved mean particle size (diameter) [mm]	**Average measured particle size [mm]**
February 19	1.12	1.05
February 20	1.02	0.96
February 21	1.06	0.97
February 22	1.18	0.98
February 23	1.04	1.02
February 24	1.08	0.86
February 25	0.98	0.94

Table 6 Comparison between diameters of ice particles retrieved with the GA and values of ice crystals size measured averaged along the vertical profile.