Robust inversion technique for retrieving soil moisture from multi-polarised backscatter of bare surface

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A robust inversion technique using a genetic algorithm (GA) for retrieving soil moisture content from the multi-polarised radar data of bare soil surfaces is presented. This inversion technique employs a semi-empirical polarimetric backscattering model as a cost function for the GA. Good agreement is found between the values estimated by this inversion technique and those measured *in situ*.

Introduction: Soil moisture content is an essential parameter in agriculture, global change monitoring, and other hydrological process. Therefore, the retrieval of this parameter from microwave satellite radar measurements has been extensively investigated. A semi-empirical polarimetric model (SEPM) has been recently introduced for microwave scattering from randomly rough bare soil surfaces [1]. The SEPM agrees not only with a combination of truck-mounted scatterometer measurements and the Jet Propulsion Laboratory (JPL) airborne SAR observations over a wide range of soil surface conditions, but also with the integral equation method (IEM) and the geometrical optics (GO) model over their individual regions of validity. The volumetric soil moisture content m_v is used as an input parameter of the model instead of the complex dielectric constant, because the backscatter depends weakly on soil type in comparison with its response to surface roughness and soil moisture. The soil moisture content m_v, therefore, can be retrieved directly from the model without an additional computation procedure to convert a dielectric constant into an *Mv* value [2].

The *vh*-polarised backscattering coefficient and the co-polarised ratio p of the SEPM is inverted directly to get the surface rms height s and the volumetric moisture content m_v together in [3]. The direct inversion method (DIM), however, fails to invert about 25% of the measurements when the values of the measured co-polarised ratio p were out of bound. The main reasons for $p > p_{max}$ are from 1. a sparse vegetation canopy over a bare soil surface, 2. a very dry surface, 3. a very rough surface, and 4. a low incidence angle [3].

In this Letter, an inversion technique using a genetic algorithm (GA) is proposed to retrieve the optimum values of the surface parameters from the measured polarimetric radar observations. This inversion technique is robust because all measurement data could yield the soil moisture contents, and the estimated soil moisture contents agree well with the data measured *in situ*.

GA-based inversion technique: The GA is a global numerical optimisation process which is patterned after the natural processes of genetic recombination and evolution, and which has advantages over other traditional optimisation techniques, because it is simple to program and does not get stuck in the local minima. The algorithm begins with a binary encoding of the input parameters, i.e. the rms height s, the correlation length l, and the soil moisture content m_v. Arbitrary 180 random chromosomes are encoded into binary sequences, and these chromosomes undergo an iterative natural selection using the SEPM to get an optimal solution.

The minimum and maximum values of the rms height, the correlation length, and the soil moisture content, are selected using the extensive field measurements from various natural bare fields. The ranges of the input parameters are selected as $0.2 \le s \le 5$ cm, $1.0 \le l \le 25$ cm and $0.02 \le m_v \le 0.4$ cm^3/cm^3, while the ranges of the field-measured input parameters are $0.32 \le s \le 4$ cm, $1.7 \le l \le 17.8$ cm and $0.03 \le m_v \le 0.29$ cm^3/cm^3.

At first, the random binary bits for the initial 180 chromosomes are generated using the sequential random numbers. Then an optimum chromosome is obtained from the initial chromosomes by an iterative computation which involves: 1. assigning merit to those chromosomes by a cost function, 2. ranking the chromosomes and discarding the inferior ones, 3. mating the superior chromosomes, and 4. mutating a small portion of the chromosomes to avoid getting stuck in the local minima.

Each binary-encoded chromosome is decoded by the formula

$$p = \sum_{i=1}^{N} b_i 2^{N-i} \frac{p_{max} - p_{min}}{2^N - 1} \qquad (1)$$

where p is one of the surface parameters (s, l or m_v), b_i is the ith binary bit ('0' or '1'), N is the number of binary bits, and p_{max} and p_{min} are the maximum and the minimum values of the parameter. The number of bits N for each input parameter is 6, which makes the quantisation error smaller than 1%.

The cost function for each chromosome is evaluated using the SEPM in [1]. At first, the polarimetric backscattering coefficients corresponding to the decoded surface parameter values of each chromosome are computed by the SEPM. Then the estimated backscattering coefficients are compared with the measurements. The cost function is defined as the summation of the weighted differences between the measured and the estimated *vv*-, *hh*-, and *hv*-polarised backscattering coefficients.

The chromosomes are ranked from the most fit to the least fit, according to their respective cost functions using a data-sorting program. Then 50% of the inferior chromosomes are discarded, and the remaining superior chromosomes mate each other.

Finally, we randomly chose about 1% of the bits in the list of all chromosomes and reverse a binary bit '1' to '0' or visa versa in order to increase the algorithm's freedom to search outside the current region of parameter space and to avoid getting stuck in the local minima. Then the cost functions are computed again, and this process is iterated for convergence.

Inversion results and discussion: For this study, the nine data sets (a total of 672 data points) are used as in [3]. The co-polarised ratio $p = \sigma^o_{hh}/\sigma^o_{vv}$ and the cross-polarised ratio $q = \sigma^o_{vh}/\sigma^o_{vv}$ are also included in the input elements of the inversion model, as well as the *vv*-, *hh*-, and *vh*-polarised backscattering coefficients, σ^o_{vv}, σ^o_{hh} and σ^o_{vh}. Each chromosome for the GA method comprises three surface parameters, i.e. the rms height s in cm, the correlation length l in cm and the volumetric soil moisture content m_v in cm^3/cm^3. The iterative procedure produces the estimated values of the surface parameters s, l and m_v for all measured data points, and the accuracy of the estimation can be judged with a correlation between the measured and the estimated values of the surface parameters. It is shown in [3] that about 25% of the measurements in the database failed to satisfy $p < p_{max}$, and consequently the DIM failed to invert directly those measurements. However, this GA-based inversion technique uses an iterative routine to find the optimum values in the given ranges of the parameters, and succeeds for all data points. The correlation coefficients between the measured and estimated parameters for all 672 data are 0.728, 0.791 and 0.724 for the rms height s, the soil moisture m_v and the parameter ks (where k is the wave number), respectively. It should be noted that the DIM succeeds only for selected data ($p < P_{max}$), as shown in [3], for the parameters s, m_v and ks. Even though the correlation length has been included in the parameter set in this study, it was found that the inversion result for the correlation length l might not be reliable because of the difficulty for an accurate ground measurement of the correlation length l [4].

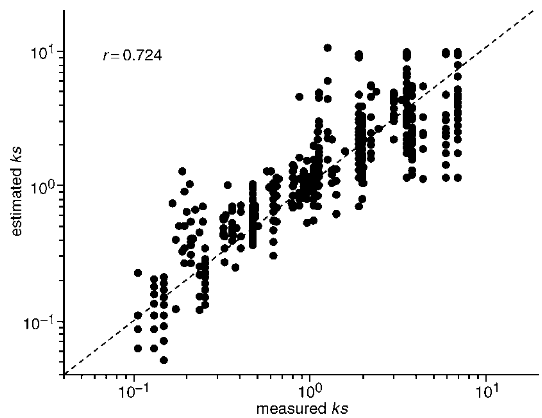

Fig. 1 *Comparison between surface parameter ks ($k = 2\pi f/c$, s = rms height) estimated by inversion technique and that measured in situ*

Fig. 1 shows a comparison between the values estimated by the inversion method and those measured *in situ* for the surface parameter *ks*. The estimated *ks* values show a relatively good correlation ($r = 0.724$) with the field-measured values as shown in Fig. 1. The GA-based inversion method is superior to the direct inversion method of [3] because the GA-based method not only succeeds in retrieving the surface parameters for all measurements but is also easier to apply to a scattering model than the DIM. Furthermore, the DIM failed on about 25% of the measurements.

Radar systems often operate at multi-frequencies and/or multi-angles. When we average the estimated surface parameters over multi-frequency and/or multi-angle data, the correlation coefficients increase. For example, if we average the estimated surface parameters over multi-frequency data, the correlation coefficients of the rms height and the soil moisture content, 0.728 and 0.791, increase to 0.874 and 0.885, respectively. When we average again the estimated parameters for multi-angle data, the correlation coefficients increase to 0.931 and 0.952 for the rms height s and the soil moisture content m_v, respectively. Fig. 2 shows the values of the volumetric moisture content m_v estimated by the GA-based inversion method plotted against the values measured *in situ*, for multi-frequency and multi-angle data. Fig. 2 shows that the retrieved soil moisture data agree quite well with the soil moisture measured *in situ*.

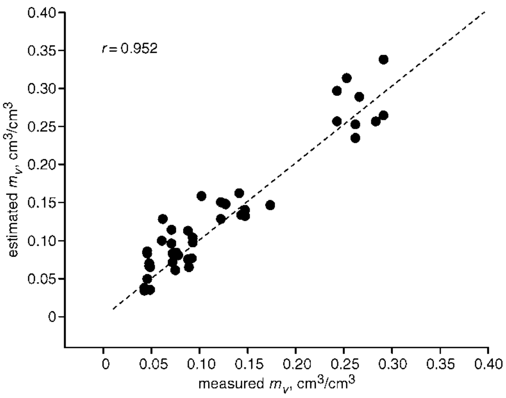

Fig. 2 *Comparison between estimated and field-measured volumetric moisture content m_v for multi-frequency and multi-angle data*

Conclusion: A robust inversion technique for retrieving soil moisture from a multi-polarised radar observation of a bare soil surface is proposed. This inversion technique employs a semi-empirical polarimetric backscattering model (SEPM) as a cost function of a genetic algorithm (GA). Good agreement was found between the values estimated by the GA-based inversion technique and those measured *in situ* for the soil moisture content m_v and the rms height s. This inversion technique is robust because all measured backscattering data succeeded in yielding the soil moisture contents without failure. The correlation coefficients between the estimated and the measured soil moisture values are 0.791 for all data, and 0.952 for multi-frequency and multi-angle data, respectively.

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