LOCAL INVERSION OF DIRECT PUSH LOGGING DATA BY INVASIVE WEED OPTIMIZATION

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ABSTRACT

A global optimization based inversion approach is presented for the interpretation of direct-push logging data. The dataset consists of natural gamma-ray intensity (*GR*), resistivity (*RES*), bulk density (*DEN*) and neutron-porosity (Φ_N) logs. By inverting this dataset, sand, clay and water content of shallow structures can be estimated and gas volume is derived from the material balance equation. By solving the local inversion with invasive weed optimization (IWO) rather than the traditionally used least squares method, the start model dependence of the procedure can be highly reduced.

1. INTRODUCTION

For the in situ investigation of shallow unconsolidated structures cone penetration tests (CPT) can be effectively applied. It is mainly used to gather information on the soil type and stratification. A technology was developed in Hungary [1], the so called engineering geophysical sounding (EGS) that can also measure gamma-ray intensity, bulk density, neutron porosity, resistivity and also the well-known parameters, cone resistance and sleeve friction. The method can be effectively used to solve several kind of problems such as mapping contaminations, assessment of environmental risks, investigation of dams and studying water resources. From EGS logs, one can get quantitative information about the composition of shallow unconsolidated sediments, such as clay content, porosity, and water content. Most methods for processing EGS data is adopted form oilfield well logging. These include deterministic, local and interval inversion methods and factor analysis [2] [3] [4] [5].

In the frame of local inversion of EGS data, the petrophysical parameters are determined for each measured depth point separately using only the data collected in that given depth point [2]. This is superior to deterministic methods, since deterministic approaches usually use only one measured log for the estimation of a given petrophysical parameter while in inversion procedures, all logs are processed simultaneously.

2. LOCAL INVERSION OF EGS DATA

The first step is the construction of the vector of model parameters. In this paper, the model is built up of clay (V_{cl}), sand (V_s), and water (V_w).

$$\vec{m} = \left[V_{\mathrm{cl}}, V_{\mathrm{s}}, V_{\mathrm{w}}\right]^{\mathrm{T}}, \tag{1}$$

where T stand for transpose. The volume of gas (V_g) is determined from the linear combination of the model parameters as

$$V_{\mathrm{g}} = 1 - \left(V_{\mathrm{cl}} + V_{\mathrm{s}} + V_{\mathrm{w}}\right). \tag{2}$$

The model parameters in Eq. 1 are the unknowns of the inversion procedure. For the calculation of theoretical logs, we have to define the response equations that connect the model parameters to the measured data. The equations for *GR*, gamma-ray intensity (kcpm), *DEN*, bulk density (g/cm^3) and Φ_N, neutron-porosity (v/v) are based on Drahos [2] and *RES*, resistivity (ohmm) is from De Witte [6]

$$GR = V_{cl} GR_{cl} + V_s GR_s, \tag{3}$$

$$DEN = V_w \rho_w + V_{cl}\, \rho_{cl} + V_s \rho_s, \tag{4}$$

$$\Phi_N = V_w \Phi_{N,w} + V_{cl} \Phi_{N,cl} + V_s \Phi_{N,s}, \tag{5}$$

$$RES = a\left(V_w + V_g + V_{cl}\right)^{-m} \left(\frac{V_{cl}/(V_w + V_{cl})}{R_{cl}} + \frac{1 - [V_{cl}/(V_w + V_{cl})]}{R_w} \right)^{-1} \left(\frac{V_w + V_{cl}}{V_w + V_g + V_{cl}} \right)^{-n}, \tag{6}$$

where rock constituents and pore fluids are *cl* (clay), *s* (sand), *w* (water) and *g* (gas). Parameters *a*, *m* and *n* are the Archie's parameters, i.e., tortuosity factor, cementation exponent and saturation exponent, respectively. These so called zone parameters are fixed during the inversion procedure. The log data calculated by the above equations are put into a vector

$$\vec{d}^{\,(c)} = \left[GR^{(c)}, DEN^{(c)}, \Phi_N^{(c)}, RES^{(c)}\right]^T, \tag{7}$$

and the measured data is also put into a vector

$$\vec{d}^{\,(m)} = \left[GR^{(m)}, DEN^{(m)}, \Phi_N^{(m)}, RES^{(m)}\right]^T. \tag{8}$$

Then these two vectors are compared and their RMS error is minimized to find the optimal values of the model vector. This problem is traditionally solved by the least squares method [7], but in this paper a different approach is presented. The distance between $\vec{d}^{(c)}$ and $\vec{d}^{(m)}$ is minimized by a global optimization method called invasive weed optimization [8].

3. LOCAL INVERSION OF EGS DATA BY INVASIVE WEED OPTIMIZATION

Invasive weed optimization is a nature inspired algorithm that is based on the colonization of invasive weeds. The algorithm itself is very simple but very effective, first, a population of weeds need to be created. Then this population is randomly spread across the entire search space. Every individual of the population represents a solution of the optimization problem.

Then to mimic natural selection, the individuals of the population are allowed to produce seeds based on the worst and best cost of the whole population and based on their own cost. The individual with the best cost produces the most seeds and the one with the worst cost produces the least number of seeds. The number of produced seeds decreases linearly from the best individual to the worst. The maximal and minimal number of seeds to be produced by the individuals is defined by the user.

The produced seeds are randomly spread across the search space using normally distributed random numbers with mean equal to zero but with varying variance. This ensures that the seeds will be placed near the parent weed. The standard deviation of the function is decreased according to Eq. 9 in the iteration process to guarantee that the probability of placing a seed in a distant area decreases nonlinearly. This condition ensures that individuals with better cost are grouped and the ones with worse cost are eliminated over time

$$\sigma_{iter} = \frac{(q_{\max} - q)^n}{q_{\max}^n} (\sigma_{initial} - \sigma_{final}) + \sigma_{final}, \tag{9}$$

where q_{max} is the maximum number of iteration steps, σ_{iter} is the value of the standard deviation in any given iteration step, q is the current iteration step, n is the nonlinear modulation index, $\sigma_{initial}$ is the initial value of standard deviation and σ_{final} is the value of standard deviation at the last iteration step.

To limit the number of individuals, a pre-defined maximum population, P_{max} is defined. When this population is reached in the iteration process, the individuals are allowed to reproduce once more and then are ranked based on their costs. The ones with better cost survive and can reproduce in the next iteration step again and the worst individuals are eliminated. This continues until the last iteration step is reached and the individual with the best cost is considered as the optimal solution of the problem.

The energy function to be minimalized by the IWO algorithm is defined as

$$E = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\mathrm{d}_i^{(m)} - \mathrm{d}_i^{(c)}}{\mathrm{d}_i^{(m)}}\right)^2} \cdot 100[\%], \tag{10}$$

where N is the number of data in one depth point. This function is minimized separately for each depth point and also characterizes the distance between the measured and calculated logs in percent.

4. INVERSION RESULTS

The IWO controlled local inversion method presented in this paper is tested on real EGS data measured in Bátaapáti, Hungary. The penetrated structures are loessy sand and loose clay. The dataset consists of natural gamma-ray intensity (*GR*), bulk density (*DEN*), neutron-porosity (Φ_N) and resistivity (*RES*) logs measured in every 0.1 m for 206 depth points. By inverting this dataset, the model parameter vector, the volume of clay (V_{cl}), sand (V_s), and water (V_w) can be estimated along the penetrated structures.

This is done by minimizing the energy function defined in Eq. 10 by the detailed IWO algorithm. First, the control parameters of IWO need to be set. All three model parameters are allowed to take values from 0 to 1. This shows that the inversion method does not need a specific start model to function properly. The initial population of 15 weeds is then generated, and the population is limited at 30 individuals. The weed with the worst cost produces 1 seed per iteration, and in a linearly increasing manner, the plant with the best cost produces 8 seeds. Equation 9 controls the placement of generated seeds, $\sigma_{initial}$ is set to 0.1 and σ_{final} is 0.001 and the *n*, nonlinear modulation index is set to 2. Then the algorithm runs thirty iterations separately for each depth point and then the individuals of the population with the best cost for each depth point is accepted as the optimal solution of the problem. An example of the decrease of the objective function defined in Eq. 10 with the iteration steps is show in fig. 1. Running the inversion process for all depth points took less than 10 seconds.

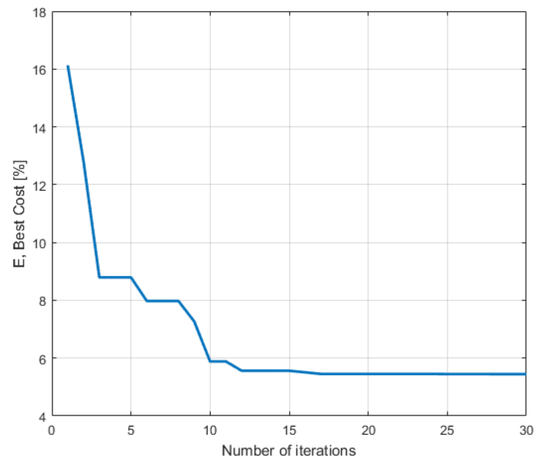

Fig. 1
Decrease of the objective function at the 206th measured depth point

Figure 2 shows the calculated (dashed line) and measured well logs (solid line) estimated by the local inversion procedure. It can be seen that the fit between most of the logs is fairly good, the mean value of the objective function for all depth points is 4.26 %.

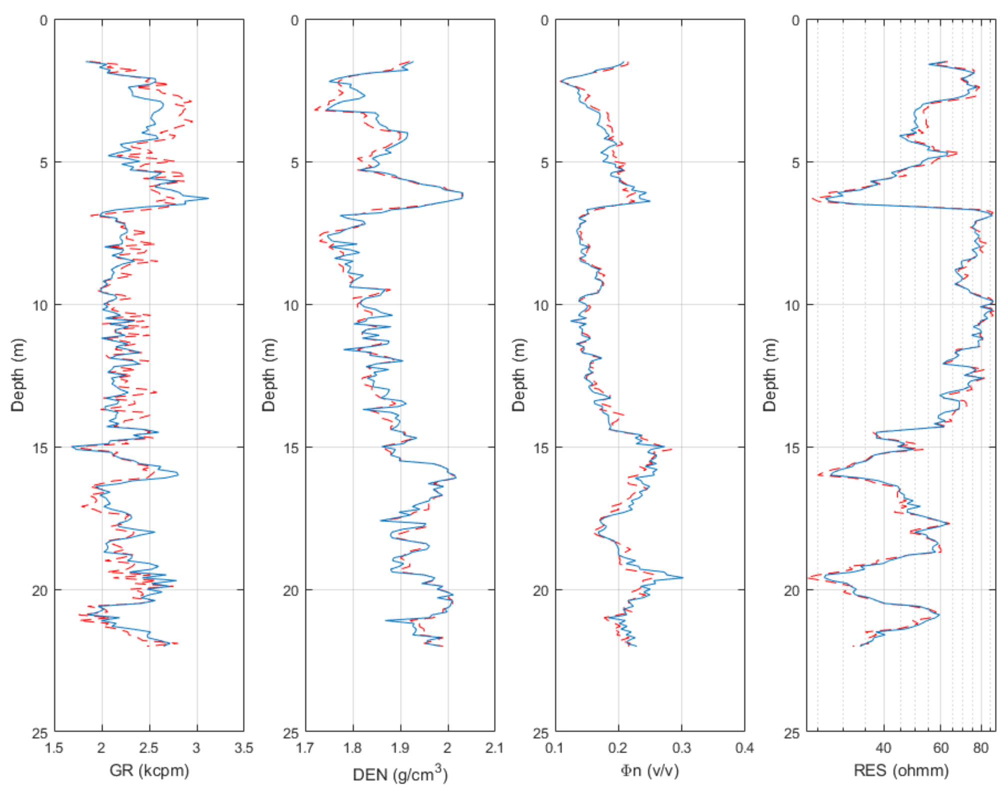

Fig. 2
The calculated (dashed line) and measured well logs (solid line)

Figure 3 shows the estimated model parameters with depth, i.e., the volume of clay (V_{cl}), sand (V_s), and water (V_w) of the investigated unsaturated formations.

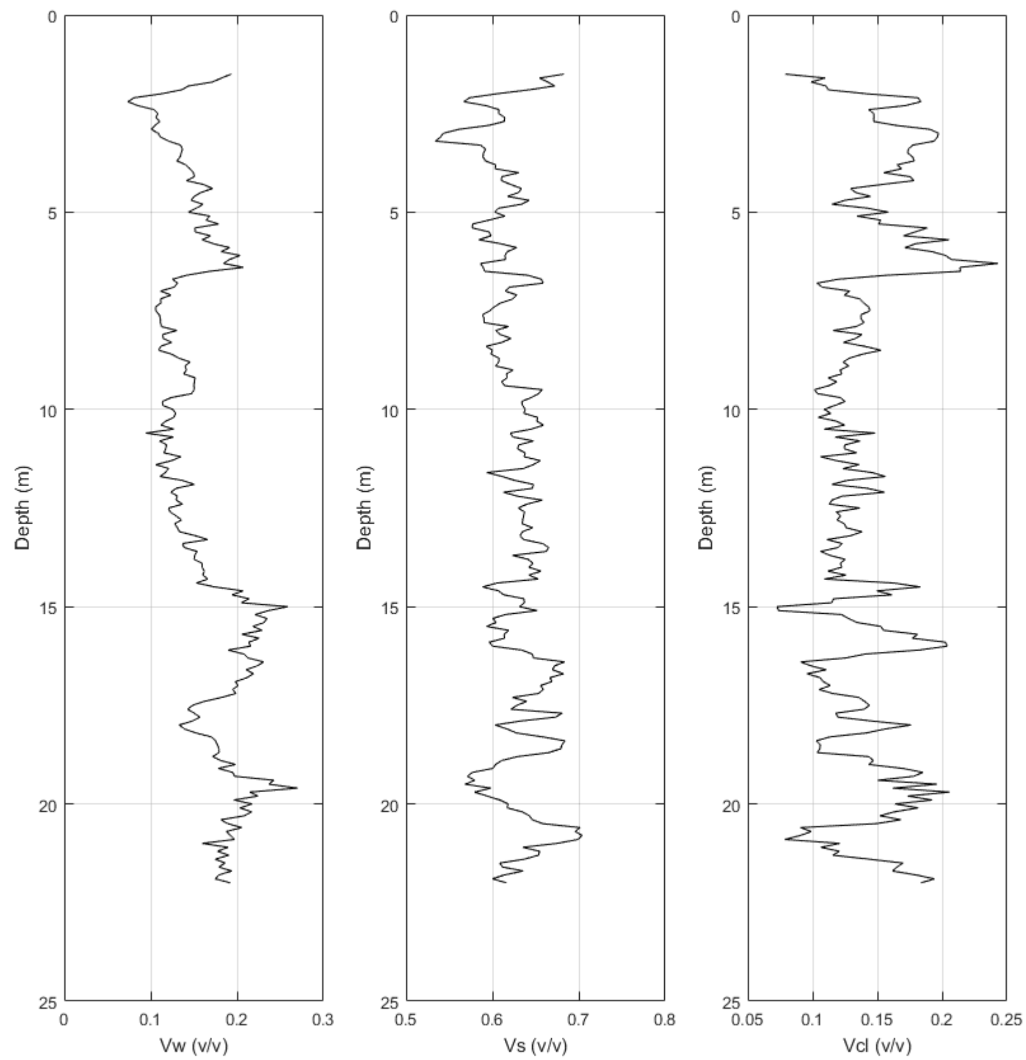

Fig. 3
The estimated model parameters by the IWO assisted local inversion of EGS data

5. CONCLUSIONS

The presented local inversion of EGS data solved by invasive weed optimization is very effective. For 206 data points it runs for less than 10 seconds, and delivers an average data distance of 4.26 % considering all data points. It does not require a specific starting model, as all unknown variables are allowed to take any value from 0 to 1. As a next step, I intend to combine this method with a linearized inversion method, and thus the estimation errors could be calculated as well.

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