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Incorporating EM Inversion into Reservoir Monitoring

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SUMMARY

In the application of controlled source electromagnetics for reservoir monitoring on land, the timelapse signal measured with a surface-to-surface acquisition can reveal the lateral extent on the surface of resistivity changes at depth in a hydrocarbon reservoir under production. However, a direct interpretation of the time-lapse signal may generally be difficult and biased. We investigated if non-linear inversion can use time-lapse responses to characterize the subsurface resistivity changes. We examined two different strategies, using a full non-linear inversion algorithm as the interpretation tool: inverting the reference and monitor data independently or in sequence. In the second case, the inversion result of the reference data set serves as an initial guess for the inversion of the monitor data set. Numerical examples show that independent inversion of the data sets can provide an estimate of the depth and lateral extent of the resistivity changes. The second strategy of sequential inversion produces less satisfactory results. We illustrate the independent inversion approach for an example with large survey repeatability errors are large and another one with a complex overburden.

Introduction

While exploration is the main application of controlled-source electromagnetic (CSEM) method these days, monitoring a hydrocarbon reservoir during production appears to be an emerging technology. Water flooding or steam injection for enhanced oil production creates resistivity changes in the reservoir, and if those changes are large enough, we can expect them to show up in the CSEM response of a time-lapse survey. Several authors investigated the feasibility of CSEM monitoring and drew the optimistic conclusion that resistivity changes due to displacing oil by brine can produce a small but measurable change in the CSEM time-lapse response (see Lien and Mannseth, 2008; Orange et al., 2009; Black and Zhdanov, 2009; Wirianto et al., 2010, and many others). Some of them, incorporating other geophysical measurements next to EM inversion, were able to use these time-lapse responses to resolve the location of resistivity changes in the reservoir (see, e.g., recent abstracts for the annual SEG and EAGE meetings).

To resolve the time-lapse resistivity changes due to displacing oil by brine, one typically uses EM inversion to produce a difference data set between the data from the initial survey and the data from the monitoring survey, which can be subsequently interpreted. There are a number of different strategies for applying non-linear EM inversion on time-lapse data, e.g., inverting the initial and monitor data independently or in sequence. The last means that the inversion result of the initial data set serves as an initial guess for the inversion of the monitor data set. Here, we investigate the effect of the two strategies on the inversion result.

Figure 1 True resistivity model plotted on a logarithmic scale. On the top, a top view of the model at depth of 1.2 km. On the bottom, a vertical cross-section at $y = 10$ km. The white triangle indicate a source location, whereas white dots the receivers location. The hydrocarbons result in a high resistivity, colored red, and the brine-filled rock leads to a low resistivity, colored dark blue. The panels on the left display the reference model, those on the right the change after production.

Model

We created a synthetic time-lapse dataset for an isotropic resistivity model. The left panels of Figure 1 shows the model. A reservoir is embedded in a $2\Omega\text{m}$ homogeneous half-space. The reservoir has dimensions of 2 km by 2 km by 500 m and consists of a hydrocarbon-bearing and a water-bearing part. The hydrocarbon-bearing part is a 300-m thick layer at a depth of 1 km below the air-earth interface and has a resistivity of $100\Omega\text{m}$. Below it, a 200-m thick water-bearing layer has a resistivity of $0.3\Omega\text{m}$. For the monitoring model, we assumed that the reservoir was flooded by saline water from the bottom at the top left corner, creating a small, 100-m thick, box-shaped depleted zone in the corner of the hydrocarbon-bearing layer. The right panels of Figure 1 shows the difference in resistivity before and after production.

We computed synthetic data sets for both models with a multigrid solver (Mulder, 2006). The top panel of Figure 1 displays the acquisition geometry. Given a source at $x = x_s$ on the surface, we measure the responses with six receiver lines on the surface with a 500 m spacing between the lines. Each line contains 82 receivers with a 100 m spacing between the stations. They are located between $x = x_s - 5$ and $x = x_s + 5$ km, excluding the short offsets between $x = x_s - 1$ and $x = x_s + 1$ km. Here, only the in-line electric components were recorded. To have both depth and lateral coverage, we used three frequencies, 10, 1, and 0.1 Hz, and five sources. We could, of course, have considered more frequencies and more sources to improve the coverage and illumination, but that would increase the required computational

Figure 2 As the right panel of Figure 1, but for the difference between the inversion result of the reference and the monitor data sets. Results in the left panel were computed independently. In the centre panel, they were computed sequentially and in the right panel, independently with a rather accurate initial model. Notice that each panel has a different color scale.

time. We did not add noise to data yet. In addition, we also assumed idealized conditions, i.e., the difference in EM response is entirely due to resistivity changes in the reservoir. Repeatability errors such as positioning errors and changes in the near surface were not yet considered.

Result

Given two data sets, the EM imaging problem of time-lapse application consists of finding two models that minimizes the weighted least-squares functional. For simplicity, we further assume that there is a change only in the conductivity and that the magnetic permeability and the dielectric permittivity are constant everywhere and time invariant.

For the optimization, we followed the approach of Plessix and Mulder (2008), employing gradient-based BFGS minimization. We applied a minimal change constraint to avoid unnecessary peaks in the solutions and used depth weighting to crudely balance the shallow and deeper resistivity updates during the inversion.

Strategy 1: independent inversion

The first strategy is to invert the reference and the monitor data sets independently. We ran the inversion twice, once with the reference data set and once with the monitor data set. We used a $2\Omega\text{m}$ homogeneous half-space as the initial model. Systematic errors may occur during the inversion. To keep them similar for both inversions, we used the same data weighting and inversion parameters for each. We observe that the two converge with almost the same number of iterations.

The resistivity differences, obtained with this strategy, are shown in the left panel of Figure 2, computed after performing 30 iterations both on the reference and the monitor data set. As can be seen, the inversion result can provide an indication of the depth and the lateral extent of the true resistivity change. However, we notice that the position of the resistivity changes is slightly shifted to the center of the reservoir. Using more sources, receivers, and frequencies may improve the result, but at the expense of more computation time. The usually poor resolution of the low-frequency EM methods also affects the monitoring case.

Strategy 2: sequential inversion

The second strategy is to invert time-lapse data set subsequently: we first invert the reference data set and then use the result as an initial guess for inverting the monitor data set. We ran the first inversion for 20 iterations, when the misfit reached about 1% of its initial value. We then started the second inversion, using the first inversion result as the initial model. The central panel of Figure 2 displays the resistivity differences. Here, we are comparing the retrieved model of the second inversion to the one of the first

inversion. It can be seen that the resistivity differences obtained with this strategy hardly indicate the true resistivity changes.

As a further test, we restarted the inversion of the reference data set with the same initial model as the inversion of the monitor data set. This approach is similar to the first strategy but now with a rather accurate initial model. The right panel of Figure 2 displays the resistivity differences. Here, we compare the inversion result of the reference and the monitor data set after 9 iterations. It can be seen that the inversion result provides an indication of the depth and the lateral extent of the true resistivity change.

Noise

So far, we assumed idealized conditions, i.e., the time-lapse data differences are entirely due the resistivity changes in the reservoir. In practice, repeatability errors will pollute the time-lapse measurements. Next, we investigate the effect of repeatability noise on the inversion result of the time-lapse data. We use the same approach as Wirianto et al. (2010), mimicking repeatability errors by adding random complex numbers to the measured electric fields. We assume repeatability errors with a maximum amplitude of 5%, relative to the signal strength at each receiver, which is slightly higher than used in Wirianto et al. (2011).

In this example, we adopted the first strategy, inverting each data set independently and comparing the inversion results at the same iteration count. We observed that the presence of repeatability errors in the monitor data set slows down the decrease of the misfit. Figure 3 shows the resistivity differences after 30 iterations. Again, we see that the inversion result still provides an indication of the depth and the lateral extent of the true resistivity change.

SEG/EAGE Overthrust model

The SEG/EAGE Overthrust model (Aminzadeh et al., 1997) provided a template for a realistic and complex subsurface. Originally, this model consists of velocity values, designed for simulating seismic wave propagation. To study whether the complexity of model affects the inversion of the EM monitoring problem, we selected this model, replacing velocities by resistivities according to $\rho = (v/1700)^{3.88}$, as suggested by Meju et al. (2003). In this 3D model, we selected one part as an artificial reservoir sand that contains oil and water. We refer to Wirianto et al. (2010) for more details about the model.

The left panel of Figure 4 displays the cross-section of the true model for the reference states. For the monitoring state, we assume that the oil-water contact has risen 100 m after water injection. We also assume a 100% sweep efficiency, meaning perfect replacement of oil by water.

We generated ‘observed’ data with those models, resulting in a reference and a monitoring data set. The acquisition involves 13 HED sources, distributed regularly along three shot-lines, i.e. at $y = 6, 8$, and 10 km. Given a source at $x = x_s$ and $y = y_s$ on the surface, we measure the EM response with six receiver lines on the surface with a 500m spacing between the lines. Each line contains 82 receivers with a 100m spacing between the stations. They are located between $x = x_s - 5$ and $x = x_s + 5$ km, excluding the short offsets between $x = x_s - 1$ and $x = x_s + 1$ km. Here, only the in-line electric components are recorded. We use three frequencies, 10, 1, and 0.1 Hz, and 13 sources, resulting in 39 source-frequency pairs. We did not add noise to the data.

We use a smoothed version of the exact model at the reference state. This is, of course, the ideal case, which in reality will require integration of several geophysical data sets. We ran two inversions — one

Figure 3 True resistivity model plotted on a logarithm scale. The hydrocarbons result in a high resistivity, colored red, and the brine-filled rock leads to a low resistivity, colored dark blue.

Figure 4 Resistivity based on the SEG/EAGE Overthrust model. On the top-left, an xy-plane cross-section of the model difference at depth of 1.45 km. On the bottom-left, an xz-plane cross-section at $y = 8$ km. The reservoir formation lies around $x = 7$ km and between 1.4 and 2.0 km depth. The dark blue part shows the injected water. The oil-bearing sand above it is coloured dark red. The black dashed lines indicate the position of the cross-sections.

with the reference data set and one with the monitoring data set — and computed the difference. The right panel of Figure 4 displays the model differences, obtained after 22 iterations. It can be seen that the resistivity changes are well retrieved at the correct depth. Some artifacts, however, appear above the reservoir. This is probably due to having an incorrect overburden model.

Conclusions

We have studied two different strategies for using non-linear EM inversion to resolve time-lapse changes due to displacing oil by brine. With the first strategy, we inverted the two data sets independently, meaning that we ran the inversion twice, once with the reference data set and once with the monitor data set. The results show that, by maintaining the same inversion parameters, the depth and lateral extent of resistivity changes due to displacing oil by brine can be recovered. The same behavior is observed when considering noise or a complex overburden. With the second strategy, we inverted the two data sets in sequence. The inversion result for the reference data set served as an initial guess for the inversion of the monitor data set. In this approach, the differences of the two inversion results hardly indicate the depth and lateral extent of the true resistivity changes. The second inversion result was substantially influenced by the initial model obtained from the first inversion.

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