Data matching of time-lapse ocean bottom node seismic using convolutional neural networks for improved repeatability

Ramon C. F. Araújo[1], Katerine Rincon[2], Pedro dos Santos[3], Gilberto Corso[4], João M. de Araújo[1], Samuel Xavier-de-Souza[5], Tiago Barros[5].

[1] Departamento de Física Teórica e Experimental, Universidade Federal do Rio Grande do Norte, Natal, RN, 59078-970, Brazil.
[2] Programa de Pós-Graduação em Engenharia Elétrica e de Computação, Universidade Federal do Rio Grande do Norte, Natal, RN, 59078-970, Brazil.
[3] Departamento de Engenharia Elétrica, Universidade Federal do Rio Grande do Norte, Natal, RN, 59078-970, Brazil.
[4] Departamento de Biofísica e Farmacologia, Universidade Federal do Rio Grande do Norte, Natal, RN, 59078-970, Brazil.
[5] Departamento de Engenharia de Computação e Automação, Universidade Federal do Rio Grande do Norte, Natal, RN, 59077-080, Brazil.

Abstract

Time-lapse seismic is the state-of-the-art technique for oil and gas reservoir monitoring. It consists of taking successive seismic surveys in the same region over time. The first survey is called baseline, and the following ones are the monitors. The not exact replication across surveys of certain factors not related to the reservoir, called non-repeatability (NR), results in spurious time-lapse data differences (4D noise) that hinder the interpretation of the production-related signal. In marine seismic, the major NR factors are changes in water velocity and positioning of sources and receivers. The problem of 4D noise can be mitigated by designing filters that correct the phase and amplitude differences between baseline and monitor data within time windows corresponding to shallow depths, in which the reservoir signal is absent. The designed filters are then applied to the full data, with the goal of reducing 4D noise while preserving the reservoir signal as much as possible. This procedure is called time-lapse data matching, and it is usually performed with matched-filter cross equalization (XEQ). Conventional XEQ requires careful picking of the time windows used for designing the filters, and it may not correct the non-linear patterns in the data imposed by 4D noise due to its linear nature. Data matching can also be approached with machine learning (ML), a technique that can extract non-linear patterns from the data, and dismisses laborious pickings. In this study, we perform time-lapse data matching of pre-stack seismic data using convolutional neural networks (CNNs). Networks are trained to match the monitor to baseline using data from shallow depths; once trained, they are used to equalize the full data. CNNs equalize one sample at a time, using as input a submatrix of monitor data centered around that sample. The use of a two-dimensional input lies on the hypothesis that the misalignments between monitor and baseline in neighboring traces (local coherence) provide useful information for equalizing a given sample. The proposed methodology is tested with synthetic time-lapse ocean bottom node (OBN) seismic data, simulated with a velocity model typical of the Brazilian pre-salt region. Results show that the proposed technique significantly reduces 4D noise: the normalized root mean square (NRMS) within the reservoir time region between the CNN-matched monitor and the monitor with perfect repeatability, calculated trace by trace and averaged across all traces, is 42% lower than the analogous metric between the monitor without matching and the monitor with perfect repeatability. Also, when migrating the CNN-matched monitor data and calculating the difference with the migrated baseline image, the time-lapse reservoir changes are much more visible and the background noise is reduced compared to the difference of monitor without matching and baseline migrated images. The main limitation of our methodology is that the equalization does not have much effect in traces where the misalignments between baseline and monitor data in large depths are very different from those in the near-surface. Further studies are necessary to assess the performance of the method on real data.