Simultaneous Multi-Vintage Multi-Parameter Time-lapse Matching

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Abstract

4D matching is an important processing step which is repeatedly used within a time-lapse processing sequence in order to remove residual amplitude, time and phase differences between vintages of seismic data. In this paper we introduce a new matching algorithm that minimizes the global NRMS between an arbitrary number of vintages and thus automatically achieves the best possible overall repeatability in one single matching step. The algorithm can work in the time- or frequency domain and simultaneously finds all matching parameters for all vintages. By using constraints a unique solution to this non-linear optimisation problem is found without the necessity to define an upfront reference vintage. This minimises the risk of propagating artefacts which may be present on one of the vintages to all other datasets. We show two example applications of the new algorithm. Firstly, we use the new algorithm for pre-imaging sail-line consistent removal of acquisition related artefacts (destriping) of multiple vintages. Secondly, we present examples of multi-vintage matching, as applicable to 4D residual local matching on imaged data.
Introduction

In time-lapse projects different vintages are acquired in different environmental conditions (tidal effects, water temperature etc.) and possibly recorded with different acquisition parameters (source and receiver depth, number of cables etc.). All these factors lead to residual amplitude, time shift and phase shift differences between vintages of time-lapse seismic data. Time-lapse matching (also known as 4D matching) is an important step in processing to remove these effects and improve the repeatability of time-lapse seismic data. Traditionally, a cascaded approach has been used in which one of the vintages has to be chosen as a reference and all the other vintages are matched to the reference. For example Zabihi Naeini and Hoeber (2008) used a least-squares time domain technique based on the Taylor expansion for time variant time shift matching. Hoeber et al. (2008) used a complex trace analysis method for 4D amplitude and phase matching. Both papers show that residual matching significantly improves the repeatability of 4D seismic data.

The motivation for this paper is to develop a new algorithm to derive all the required matching parameters at the same time as well as process all the vintages simultaneously without the need for a reference vintage (choosing a good reference upfront is not always an easy task). Zabihi Naeini et al. (2009a) recently introduced the concept of simultaneous multi-vintage time shift estimation (figure 1) in which the Lagrange multipliers method was used to incorporate “network constraints” into the least-squares Taylor technique of time shift estimation. This new approach led to the best overall repeatability between all of the vintages in comparison with the cascaded approach. Zabihi Naeini et al. (2009b) used similar principles for multi-vintage 4D binning and showed how this algorithm results in better overall repeatability when compared to cascaded 4D binning. In this paper a new simultaneous multi-vintage multi-parameter matching algorithm will be introduced.

Normalized RMS of the difference of two vintages or NRMS (Ronen et al., 1999) is a well known attribute to measure the repeatability of 2 vintages of time-lapse seismic data at each stage of processing (lower NRMS means better repeatability). For multi-vintage applications Zabihi Naeini et al. (2009b) used the L2 norm of NRMS to measure the best overall repeatability between all vintages.

In this paper, we introduce a new multi-vintage multi-parameter matching algorithm based on minimizing a similar cost function (global NRMS) using a constrained non-linear optimization approach. The additional network constraints are extended for all the matching parameters i.e. amplitude, time shift and phase shift. The advantages of our new algorithm are: 1) we no longer need to choose a reference upfront 2) we minimize global NRMS to solve for amplitude, time shift and phase shift simultaneously 3) minimizing global NRMS aims to achieve the best overall repeatability. We start by describing the methodology followed by some synthetic and real data examples.

Theory

As NRMS is not a linear function of amplitude, time shift and phase shift it is not possible to simultaneously invert for all these parameters using linear inversion algorithms. Also it is not straightforward to calculate the derivatives relative to the above mentioned parameters to build the Hessian matrix for non-linear inversion. We therefore have chosen to use a direct search optimization
algorithm to find the minimum of NRMS for a set of required matching parameters. Direct search is a method for solving optimization problems that does not require any information about the gradient of the objective function. Depending on the problem, there are varieties of methods to perform the search e.g. one of the most famous and efficient algorithms is the classic simplex algorithm of Nelder and Mead (1965) and a more recent method of search is using Genetic algorithms. Figure 2 schematically depicts the iterative progress towards the minimum of NRMS by starting from an initial point for two Ricker wavelets in which the only difference between them is due to an amplitude scalar of 0.8 and time shift of 3 ms. As mentioned in the previous section, our objective function is the multi-vintage global NRMS which can be either the L2 norm NRMS or simply the average NRMS of multi-vintages of a time-lapse project. The desired solution is a set of matching parameters (amplitude \(a\), time shift \(\tau\), and phase shift \(\phi\)) for each vintage which minimizes the objective function. We found the Nelder-Mead method sufficient for our optimization problem. The Nelder-Mead algorithm iteratively reaches to the optimal point by replacing the worst vertex with a new point at each step of downhill process using three major operations known as reflection, expansion and contraction (Nelder and Mead, 1965). After each step we restart the process with a new simplex until the termination criterion is achieved.

An important step is to constrain our optimization problem to find a unique solution. In our case, we are looking for a set of matching parameters to match multi-vintages of a time-lapse dataset. We use network constraints which state that the estimated time shift, phase shift and amplitude must form a closed loop (or in other words, in the case of time shift for example, the average applied shift is zero). In general, this can be written as:

\[
\sum_i \{\log(a_i), \tau_i, \phi_i\}=0
\]  

(1)

where subscript \(i\) varies from 1 to total number of vintages. For the 3-vintage case this can be simplified to:

\[
\tau_1+\tau_2+\tau_3=0; \ \phi_1+\phi_2+\phi_3=0; \ \log(a_1)+\log(a_2)+\log(a_3)=0 \ \text{or} \ a_1a_2a_3=1
\]  

(2)

It can be observed that in this approach there is no need to define a reference vintage as all the vintages are changing to minimize global NRMS subject to additional network constraints. Although in this paper we are focused on the benefits and applications of network constraints, it is worth mentioning that technically it is possible to define a reference vintage (this is a constraint itself).

**Synthetic examples**

The first synthetic example demonstrates how the algorithm works for a simple 3-vintage case where each vintage consists of a single Ricker wavelet with different amplitude, time shift and phase shift relative to a reference (here vintage 1). The top row in figure 3 is the case where different vintages have different a) amplitudes, b) time shift, c) phase shift, d) amplitude and time shift and e) amplitude, time shift and phase shift. The result after simultaneous multi-vintage matching is shown in the bottom row respectively. It can be observed that all the vintages are nicely matched by minimizing global NRMS as well as satisfying the network constraints (shown for the first 3 scenarios).

Another example is to demonstrate the problems in choosing a reference when the reference vintage (for example a legacy base) contains some time shift jitters. We compare the result after matching to a chosen reference with the result after using the simultaneous matching algorithm introduced in this paper. Figure 4a shows a 3-vintage example where we choose the base dataset as a reference and match the other vintages to the base using the classic method of crosscorrelation time shift matching (figure 4b). The result after our new technique (figure 4c) shows that incorporating network constraints leads to an optimal solution for both 3D and 4D data quality i.e. it produces the same 4D differences and also it avoids introducing time shift jitters from one vintage to the others.

**Real data examples**

In this section we show the benefits of the proposed algorithm for pre-imaging and post-imaging
matching applications. Local matching before migration can degrade the 4D signal but at the same time the residual acquisition footprints can lead to migration artefacts in the 4D difference section. We introduce a sail-line consistent destriping method based on our proposed algorithm for pre-imaging matching i.e. before data regularization when sail-line information is still available. In this method, the matching parameters are derived in such a way that they are smooth along the sail-lines to only correct for global acquisition related stripes. Figure 5 shows an example RMS ratio map between 2 vintages of 5-vintage Gullfaks dataset before and after our sail-line consistent destriping method where it can be observed that the acquisition related stripes are nicely removed.

Figure 4 (a) Raw input including a jittery base and two monitors with a relative global shift. (b) Output after crosscorrelation time shift matching of monitors to the base (resulting in zero 4D differences). (c) Output after simultaneous multi-vintage (SMV) matching without a reference where all the vintages are optimally matched in both 3D (jitters are not introduced from the base to the monitors) and also 4D sense (the 4D differences are zero).
We also applied the proposed algorithm on the Gullfaks dataset for local matching after migration. In local matching, we have one set of matching parameters for each trace and each vintage. Figure 6 shows two example 4D difference sections before and after simultaneous multi-vintage matching. The example demonstrates a nice improvement in repeatability without affecting the 4D response.

Conclusions

We propose a new simultaneous multi-vintage multi-parameter matching algorithm based on a constrained non-linear optimization method. Global NRMS was chosen to achieve the best overall repeatability between all vintages. In addition we also incorporated additional network constraints in order to maintain a good 3D image. The algorithm was tested on synthetic and real data for local matching and sail-line consistent destriping applications.

Acknowledgments

The authors would like to thank CGGVeritas for permission to publish this paper and Statoil for permission to show the real data examples.

References