

Tracking 3D seismic horizons with a new hybrid tracking algorithm

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Abstract

We have developed a new algorithm for tracking 3D seismic horizons. The algorithm combines an inversion-based, seismic-dip flattening technique with conventional, similarity-based autotracking. The inversion part of the algorithm aims to minimize the error between horizon dips and computed seismic dips. After each cycle in the inversion loop, more seeds are added to the horizon by the similarity-based autotracker. In the example data set, the algorithm is first used to quickly track a set of framework horizons, each guided by a small set of user-picked seed positions. Next, the intervals bounded by the framework horizons are infilled to generate a dense set of horizons, also known as HorizonCube. This is done under the supervision of a human interpreter in a similar manner. The results show that the algorithm behaves better than unconstrained flattening techniques in intervals with trackable events. Inversion-based algorithms generate continuous horizons with no holes to be filled posttracking with a gridding algorithm and no loop skips (jumping to the wrong event) that need to be edited as is standard practice with autotrackers. Because editing is a time-consuming process, creating horizons with inversion-based algorithms tends to be faster than conventional autotracking. Horizons created with the adopted algorithm follow seismic events more closely than horizons generated with the inversion-only algorithm, and the fault crossings are sharper.

Introduction

Because horizon tracking is an essential, difficult, and time-consuming part of seismic interpretation, numerous algorithms and workflows have been developed since the introduction of seismic interpretation workstations in the 1980s. The first landmark paper on horizon tracking only considered amplitude values to follow seismic peaks, troughs, and zero crossings (Howard, 1991). This method works well for fairly continuous reflectors but it breaks down in more difficult conditions such as in the presence of faults and with laterally changing reflectors. A good summary of the early history of horizon tracking is given by Dorn (1998). A significant improvement was the introduction of crosscorrelations, which enable tracking across faults (e.g., Admasu and Tönnies, 2004; Aurnhammer and Tönnies, 2005).

The introduction of global seismic interpretation methods revolutionized seismic interpretation workflows in the past decade and increased the amount of geologic information that is extracted routinely

nowadays from the data (de Groot et al., 2016). Global seismic interpretation methods can be defined as automated or semiautomated methods that aim to generate fully interpreted volumes (Stark, 2004; Lomask et al., 2006; de Groot et al., 2010; Hoyes and Cheret, 2011; Dirstein and Fallon Gary, 2012; Labrunye and Jayr, 2013; Stark et al., 2013). The fully interpreted volumes created by these methods increase our understanding of depositional histories and are instrumental in finding stratigraphic traps, and these algorithms enable the construction of more accurate geologic models in less time.

Global methods differ in the way they correlate seismic events, in how they store results (in a regularly sampled volume, or as a dense set of horizons), and in the way, and amount, of user interaction. Based on technology, global methods can be grouped into three categories:

- 1) event correlation
- 2) artificial intelligence (AI)
- 3) flattening.

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Each method has its pros and cons. Methods based on event correlation evolved from conventional amplitude and similarity trackers. The modern variant is inversion based (Pauget et al., 2009). It outputs a 3D grid model by connecting each seismic event (min, max, and zero crossings) to the most probable neighboring events. Event-correlation-based methods are robust but are also prone to loop skips (jumps to erroneous events), which require human intervention. Furthermore, event-based techniques struggle with correlating laterally varying events such as unconformities, which are key events in seismic sequence stratigraphic analysis.

Methods based on AI, especially those using deep-learning algorithms, show potential (Grimsgaard, 2019; Gupta et al, 2019), but more research and development is needed before these methods reach the market and can be applied in operational settings. AI methods require large amounts of (accurate) training data, which are difficult to generate. Furthermore, training deep learning algorithms is a time-consuming process. Finally, results need checking and editing manually by the user, which is also time-consuming. A global seismic interpretation method based on AI is already on the market. Dirstein and Fallon Gary (2012) use genetic algorithms to output horizon patches that are locally accurate, but the patchy nature of the output limits its usefulness. Bugge et al. (2019) present a combination of supervised and unsupervised learning methods and dynamic time warping (Hale 2013) to produce horizon patches in regions with extensive faults. Their workflow is fully automated, but the results also require checking and editing.

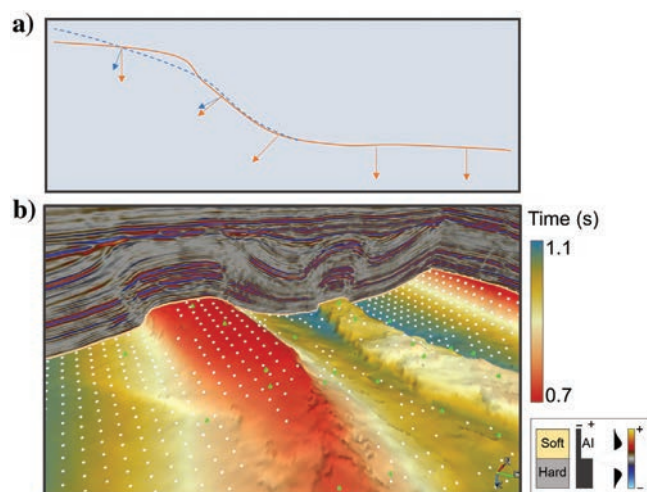


Figure 1. Principle of the hybrid tracker: (a) An inversion algorithm minimizes the error between horizon grid dips (blue) and precomputed seismic dips (orange), and (b) the horizon grid is tied to manually picked seed positions (the green dots) and autogenerated seeds added by the similarity-based autotracker after each inversion cycle (the white dots).

Flattening methods are inversion-based techniques that aim to flatten the seismic dip field (Lomask et al., 2006; de Groot et al., 2010; Wu and Hale, 2013). Because these methods do not operate on seismic amplitudes but instead use the dip field as input, they are capable of mapping unconformities. A disadvantage of flattening is that the resulting horizons are not necessarily phase-consistent. In other words, horizons may drift around seismic events instead of following these exactly. To overcome this problem, Wu and Fomel (2018) combine local reflection slopes (Hale, 2009; Yu et al., 2012) and multigrid correlations obtained by dynamic time warping (Hale, 2013). The horizons shown in Wu and Fomel's paper indeed seem to be phase-consistent, but we were not able to achieve the desired level of phase consistency in our own experiments with this algorithm. Therefore, we decided to develop an alternative method, which is presented hereafter as the hybrid algorithm.

Horizons generated with inversion-based flattening algorithms are continuous; that is, they exist at every seismic position where dip information exists. Conventional autotrackers usually require filling holes and editing loop skips. Filling holes with a gridding algorithm is inaccurate, and editing is time-consuming and laborious. The workflow for inversion-based flattening is faster. The interpreter performs quality control (QC) on the horizons, adds seeds where needed, and reruns the inversion until satisfied. The inversion itself is fast and parallelized. To create four horizons in the Delft survey (84 km²) took 40 s on a Windows 10 machine with four 2.5 GHz cores and 32 GB RAM.

The algorithm discussed in this paper is a hybrid method that combines inversion-based flattening with event correlation. We will compare the proposed hybrid algorithm with the underlying algorithms: inversion-based flattening and similarity-based autotracking. We will show that the hybrid method improves phase consistency in intervals with correlatable events. Furthermore, we will argue and demonstrate that both inversion-based algorithms are needed in the creation of a dense set of horizons for the example data set.

Methodology

The inversion-based flattening part of the hybrid algorithm is an implementation of the algorithm proposed by Wu and Hale (2015). An initial horizon grid is constructed through one or more seed positions, after which an inversion algorithm minimizes the error between horizon dips and seismic dips (Figure 1a). This is done with a constrained conjugate gradient solver. After each iteration loop of the solver, the horizon grid is retied to the input seeds (Figure 2, the gray blocks). Seismic dips are precomputed with a principal component analysis (PCA)-based algorithm that outputs local dips in the inline and crossline directions. Prior to inversion-based flattening, the dip field is usually smoothed and denoised with a median filter. Optionally, the PCA-based dip computation algorithm outputs a third

component called “planarity” (Wu and Hale, 2013). Planarity is a measurement of the local curvedness of the dip field normalized between 0 and 1. High planarity corresponds to good reflections. Low planarity occurs near faults and in noisy sections. Planarity is used by the inversion algorithm to assign higher weights to areas with good reflections.

The similarity-based autotracker in this paper starts from one or more manually picked seed positions that are snapped to a seismic event. The tracker compares the (relative) amplitude differences and crosscorrelations between seed traces and traces located at the edges of the growing horizon grid. Positions are added to the grid if the acceptance criteria are met. This tracking mode is used in the exercise in which we compare the three algorithms (the next section). In the hybrid algorithm, the decision to add seed positions is based not on relative amplitude differences but only on crosscorrelation thresholds.

In the hybrid tracker, the two algorithms are combined (Figure 2, the gray and yellow blocks). Again, the horizon is constrained with one or more manually picked seeds. In contrast to the inversion-based flattening on dip only, the hybrid algorithm snaps seed positions to the nearest event, that is, either to a maximum or a minimum. An initial horizon grid is constructed through the seed positions, and the conjugate gradient solver is started. After each inversion cycle, the similarity autotracker kicks in to add additional (snapped) seed positions (Figure 2). The horizon grid is tied to the new seeds, and the process continues until the end criteria of the inversion loop are met.

Netherlands data set

The data set is a time-converted subset of a 3D prestack depth migration (PSDM) volume covering the city of Delft. The data were acquired in 1985 by NAM and were reprocessed in 2011. The bin size is 20 m by 20 m, and the temporal sampling rate is 4 ms. The data are zero-phase, non-SEG polarity, meaning a hard kick is a negative number. The areal coverage of the subset is 84 km².

Oil and gas have been produced in this area since the 1950s, but most onshore fields were abandoned around 1994. Oil was produced from early Cretaceous sands, whereas gas was produced from Germanic Triassic sandstones of the Bundsandstein subgroup. With the Netherlands’ drive toward renewable energy, the interest in exploring for oil and gas has now shifted toward geothermal energy. In the study area, two geothermal systems have been operational since 2010 and a third installation is being planned.

Results

Figure 3 shows three horizons created with the hybrid algorithm. The upper horizon (pink) is the Base Upper North Sea, an important break in sedimentation around the Oligocene-Miocene boundary. The group consists of shallow-marine sediments, mainly deposited in the western Netherlands, and of terrestrial beds of fluvial, paralic, and lacustrine origin. In the upper part, glacial deposits occur (DINO, 2019). The boundary corresponds to a hard kick and is displayed as a white loop. The event was tracked through the entire survey from one seed only. The middle horizon (orange) is a hard kick in the Holland Formation, consisting of marine deposits of marls, clays, and sandstones. The mapped intra-Holland event shows up as a clear white

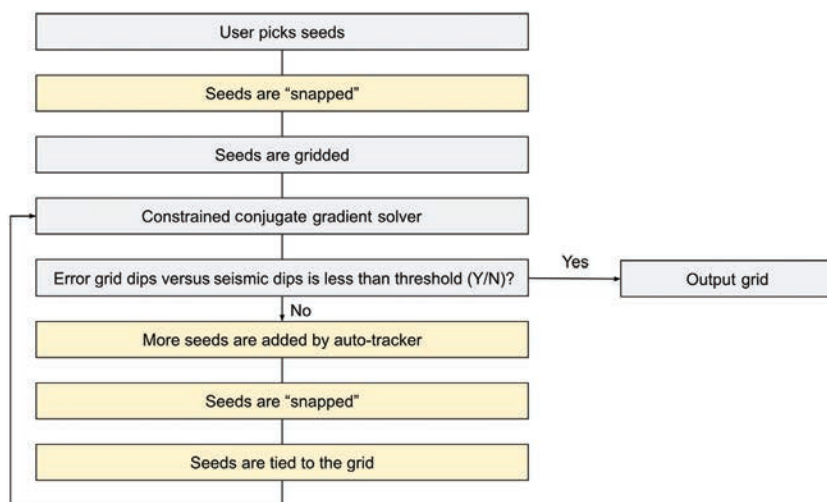


Figure 2. Flowchart of the two inversion-based algorithms described in this paper. The unconformity tracker only executes the gray colored steps. The hybrid tracker also executes the yellow steps.

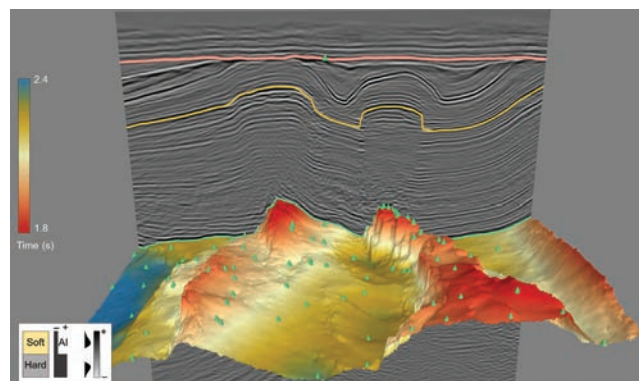


Figure 3. A seismic section with three horizons tracked by the hybrid algorithm. The upper horizon (the base Upper North Sea, salmon color) was tracked from a single seed position. The middle and lower horizons (intra-Holland [orange] and deep event [green], respectively) were tracked with multiple seeds and required several QC runs in which seeds were added.

loop that was tracked from two seed positions. The deepest event is also picked on a white loop, but this event is more difficult to track. The lateral continuity varies, and the interpretation had to be forced through the faulted zones under the popup structures where the seismic quality is poor. To track this horizon required several iterations and dozens of seeds. Even so, the workflow was considered to be easier and faster than tracking with a conventional autotracker with inherent editing and postinterpretation infill gridding problems.

Figure 4 shows a comparison of the three algorithms on the deep event depicted in Figure 3. All of the algorithms used the same set of input seeds. The inversion-based algorithms used the same inputs (seismic dips plus planarity) and input parameters for the conjugate gradient solver. The similarity-based tracker tracked on the basis of relative amplitude differences and crosscorrelation thresholds. The parameters were optimized to track as far as possible without creating loop skips. Nevertheless, as can be seen in Figure 4, the tracker did create some loop skips and left holes to be filled. The problem of loop skips can be reduced, albeit at the expense of creating larger holes. If we compare the two inversion-based algorithms with each other,

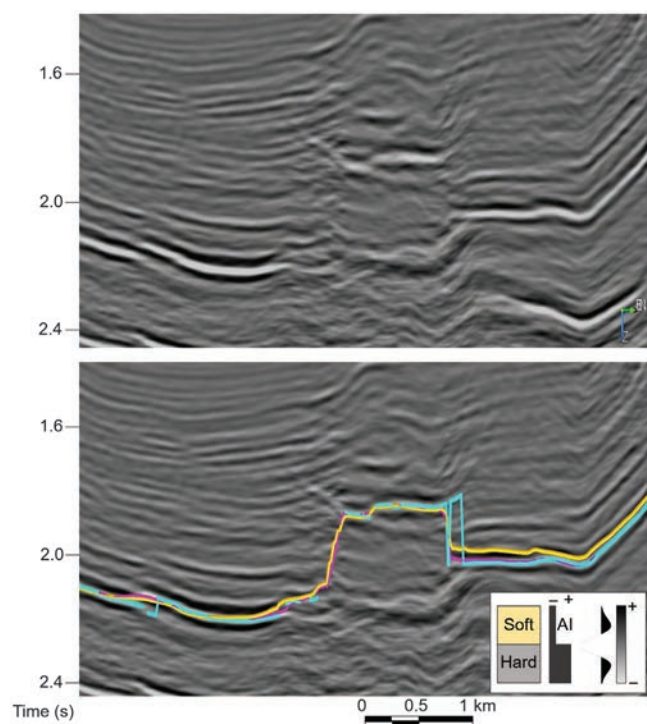


Figure 4. Comparison of tracking algorithms: hybrid algorithm (pink), inversion-based flattening on dip only (yellow), and amplitude and similarity tracking (light blue). Note the loop skips and holes in the amplitude and similarity tracked horizon and phase inconsistency of the inversion-based flattening on dip only. The latter is most clearly seen on the right side where the horizon drifts around a black loop instead of staying on the white loop it is supposed to follow.

we observe that the hybrid tracker better follows the white loop than the tracker that is based only on flattening the dip field.

The dense set of horizons was created by the user in three consecutive interpretation steps. First, the user created a set of framework horizons that divided the interval of interest into a manageable set of sequences. Framework horizons can be imported, or they are tracked by one of the algorithms described in this paper. Because framework horizons represent relative geologic timelines, the only criteria imposed on them are that (1) they must be continuous (meaning they have a Z value at every grid position) and (2) they cannot cross each other. Figure 5b shows six framework horizons that split the interval above the Top Vlieland (framework horizon 6) into five sequences. The Base Tertiary event (framework horizon 3) is a pronounced unconformity with laterally varying reflection patterns. This event was tracked with the inversion-based flattening algorithm (dip only). The top horizon is a dummy horizon at $Z = 0$ ms. The four other framework horizons are trackable events that were mapped with the hybrid algorithm.

The next step in the workflow is infill tracking under human supervision. This is done per sequence bounded by framework horizons. The workflow is similar to the one described above: The inversion-based algorithm is run (either dip only or hybrid), the results are QC-ed, and additional seeds are added. This is repeated until the user is satisfied with the infill horizons in the sequence after which the process is repeated for all sequences. The algorithm ensures that all horizons are continuous and that none of the infill horizons crosses the framework horizons, or each other (Figure 5c).

In the third and final step, more horizons are added to the set to arrive at the desired density for follow-up work including but not limited to Wheeler transformation (seismic flattening), model building, and seismic sequence stratigraphic interpretation. Infilling at the finest level can be done with the same methods applied in the previous step, but in this case, it was done with a model-driven algorithm that inserted horizons proportionally between the upper and lower bounding horizons (Figure 5d). All of the horizons, whether created by inversion-based methods or by model-driven infill, in the set are continuous, and no horizon crosses any other horizon in the set. Because of these properties, each horizon in the set can be considered a relative geologic timeline. In other words: A horizon located above another horizon in the same set is by definition younger than a horizon located below. The accuracy of the set is fully user-controlled. First, the user controls the accuracy of the framework horizons by rerunning the inversion-based algorithms until satisfied. Second, the user controls the amount, and accuracy, of infilled horizons. More accuracy is obtained by adding more inversion-based infill horizons and rerunning the algorithm until satisfied.

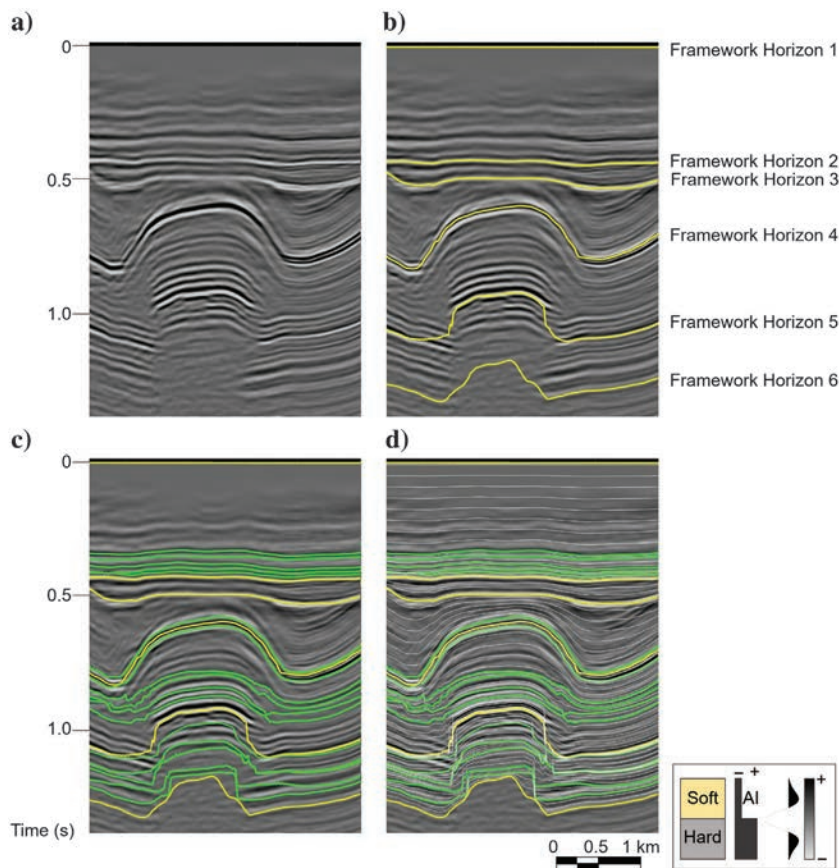


Figure 5. Stepwise creation of a dense set of horizons: (a) inline 2588, (b) framework horizons (yellow), (c) user-guided infill horizons (green), (d) model-driven infill horizons (white; every fourth horizon is shown).

Conclusion

We introduced a hybrid algorithm that can be used to (1) quickly generate a set of seismic horizons and (2) create a dense set of horizons. The hybrid algorithm performs better on trackable events than an inversion-based flattening algorithm that only operates on the dip field. The latter is better at tracking laterally varying events such as unconformities (de Groot et al., 2016). Both inversion-based algorithms tend to generate seismic horizons faster than similarity-based autotrackers. This is because inversion-based algorithms produce continuous horizons that do not require time-consuming loop-skip editing and inaccurate infill gridding. Instead, the interpreter iterates a workflow of three steps: adding seeds, running the inversion, and QC-ing results, until satisfied.

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Data and materials availability

Data associated with this research are available and can be accessed via the following URL: <https://www.nlog.nl/>

[.nl/](https://www.nlog.nl/). The paper's data set was a proprietary data set from Hydreco Geomec BV. The NLOG site is a portal with public domain data from The Netherlands. The portal has 3D seismic and well logs in the study area, but authors cannot guarantee that the processing is the same as in the paper's data set.

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Interpretation / November 2020 7