Exploring seismic data in the flowline domain: Automated extraction of unconformities, sequence boundaries, and conformable reflections

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Abstract

Working with seismic data in the flowline domain offers a promising approach to improving geologic interpretation, particularly in identifying unconformities and sequence boundaries. This method utilizes the seismic differential dip field as a fluid velocity field to extract geometric information and generate flowlines. These flowlines, treated as distinct objects, represent the paths of hypothetical particles moving along local velocity vectors within the seismic data. By applying a scoring system based on overlapping paths, major unconformities and sequence boundaries can be efficiently identified and extracted. An additional advantage of the flowline representation is its ability to capture the lateral regional context of seismic geometries, enabling straightforward grouping into stratigraphic sequences through simple clustering techniques, which simplifies the categorization of first-order stratigraphic units. Furthermore, refining the flowline paths based on relative amplitude changes improves their alignment with conformable reflections, supporting a flowline-based approach to effectively track these reflections. The flowline approach can also be extended into three dimensions, providing a straightforward tool for preliminary geologic analysis in 3D seismic data. The flowline-based workflows are demonstrated through application to two seismic sections, one of which addresses challenges posed by faulted areas and showcases the strategies used to resolve them.

Introduction

Seismic reflection data provide images of the earth's subsurface, allowing geologists to map geologic structures and interpret processes such as sedimentation history and tectonic activities. Mapping these structures from seismic images requires significant time and expertise in seismic interpretation and geophysical understanding. Each seismic image reveals unique stratigraphic sequences, characterized by variations in reflection properties like continuity, amplitude, and frequency spacing (Badley, 1985).

These seismic sequences represent stratigraphic units consisting of conformable seismic reflections, indicating periods of consistent sedimentation conditions influenced by factors such as sediment supply and relative sea level. The boundaries of these sequences, defined as unconformities or correlative conformities, mark changes in sediment deposition or nondeposition (Mitchum et al., 1977). Furthermore, seismic sequences can be categorized into depositional strata packages, such as low-stand, high-stand, and transgressive system tracts, offering valuable insights into the evolution of sedimentary basins (Vail and Mitchum, 1977). Understanding these stratigraphic units and their boundaries is fundamental to unraveling the evolution of sedimentary basins.

Since the mid-1990s, autotracking tools for seismic interpretation have been readily available through standard industry software packages (Henderson et al., 2007; Pauget et al., 2009; Marroquín, 2014; Eckersley et al., 2018; Vevle et al., 2018; Williams, 2018). However, despite these tools, seismic interpretation still heavily relies on the manual efforts of experienced interpreters. Several notable computational and computer-assisted horizon extraction methods have emerged, including techniques using unwrapped instantaneous phase volumes (Stark, 2003, 2005; Wu and Zhong, 2012) and methods based on local reflection slopes (Bakker, 2002; Lomask et al., 2006; Wu and Hale, 2013; Wu and Fomel, 2018). Although many data-driven methods for horizon extraction successfully track coherent horizons, they struggle to correlate dislocated horizons across faults and along unconformities within complex seismic volumes. Addressing unconformities resulting from significant erosion poses particular challenges, as they often truncate seismic horizons. Unconformities are crucial for understanding sedimentary basin evolution, typically indicating changes in depositional environments due to erosional events or hiatuses. Their interpretation can be labor-intensive, especially using traditional seismic interpretation methods. Over recent decades, various methodologies leveraging computer science, including image processing and machine learning, have been proposed to automate this process (Bahorich and Farmer, 1995; Barnes, 2000; van Hoek et al., 2010; Wu and Hale, 2016).

In this paper, we explore various aspects of working with seismic data in the flowline domain. This approach involves converting seismic data into flowlines by tracing the trajectories of imaginary particles within the differential dip field of the seismic image. One of the key advantages of the flowline representation is that it seems to be highly suitable for identifying and tracking sequence boundaries and unconformities, which can be hard to track using correlation-based approaches. In the flowline representation, unconformities and sequence boundaries are identified as regions where flowline paths converge. This allows us to create simple workflows for automatic identification and extraction of these otherwise hard-to-track seismic features.

Our approach builds upon existing methodologies that delineate seismic horizons by tracking the local dip of seismic events, as demonstrated by de Bruin et al. (2006) and van Hoek et al. (2010).

However, rather than primarily deriving secondary attributes, we focus on the direct analysis and interpretation of seismic data within the flowline domain.

In the following sections, we first detail the process of converting seismic data into the flowline domain, which forms the foundation for the subsequent workflows. We then explore how this representation enhances geologic interpretation through several workflows. First, we describe the extraction and ranking of seismic sequence boundaries and unconformities using a sorting and filtering algorithm. We also present a cluster-based approach that groups similar flowlines to assist in identifying sequence boundaries and their associated subsequences. By introducing an amplitude constraint, in the form of an amplitude likeness criterion, we demonstrate that the flowline representation can be used to track conformable reflections.

Additionally, we introduce a straightforward pseudo-3D approach to extend the flowline methods, taking a step toward making these workflows applicable to 3D seismic data. Finally, we apply the workflows to two case studies from the Barents Sea, including an oil field, discussing the challenges of the flowline representation in tectonically complex areas and proposing strategies to address them.

Methodology

To characterize the dip field, we adopt a similar approach to van Hoek et al. (2010) where we estimate the dip field based on the structure tensor. The structure tensor, denoted as S, is defined by its eigenvalues $\lambda_1 > \lambda_2 > 0$ and the corresponding eigenvectors $\{e_1, e_2\}$, which can be written as

$$S = \lambda_1 e_1 e_1^T + \lambda_2 e_2 e_2^T. \quad (1)$$

The largest eigenvalue, λ_1, and its eigenvector, e_1, are aligned perpendicularly to seismic reflections, indicating maximum gradient alignment. The smallest eigenvalue, λ_2, with its orthogonal eigenvector, e_2, aligns parallel to seismic reflections, which is central to our analysis.

In our study, we treat the differential dip field aligned parallel with the seismic reflections (e_2) as a fluid velocity field $V(x, y)$, which describes the local flow velocity vector at each point (x, y). This resulting velocity field is static and does not change with time, as it is derived from the fixed amplitude image, making it analogous to a steady flow. Flowlines are the curves whose tangents are everywhere parallel to the fluid velocity field at all points (Chung, 2010). The velocity vector field in $\mathbb{R}^2$ can be represented using the unit vectors along the x and y axes, given by $\hat{i}$ and $\hat{j}$, respectively. Thus, the velocity field is given by

$$V(x, y) = u\hat{i} + v\hat{j}, \quad (2)$$

where the velocity components in the x and y directions are given by $u = u(x, y)$ and $v = v(x, y)$, respectively (Anderson, 1995). By placing an imaginary particle in this velocity field, we can trace the flowline by tracking the particle's movement, which will follow the direction of the velocity vector at each point along its path, effectively mapping out the flowline. To characterize the geometry of a flowline, we define an infinitesimal arc-length vector along the flowline, denoted as

$$d\vec{s} = dx\hat{i} + dy\hat{j}, \quad (3)$$

where dx and dy are the infinitesimal displacement in the x and y direction, respectively. Because the flowline should be parallel to V, the following must be true:

$$d\vec{s} \times V = (v\,dx - u\,dy)\hat{k} = 0. \quad (4)$$

Rearranging equation 4, we can formulate it as an ordinary differential equation (ODE):

$$\frac{dy}{dx} = \frac{y}{x} = \frac{v(x,y)}{u(x,y)}. \quad (5)$$

Using the components of our differential field $u(x,y)$ and $v(x,y)$ and a point (x_o, y_o) through which the flowline passes, we can formalize the integral for the flowline as follows:

$$y(x) = \int_{x_o}^{x} \frac{v(x,y)}{u(x,y)} dx + y_o. \quad (6)$$

In practice, we obtain the flowline by solving the ODE numerically using the fourth-order Runge-Kutta method (RK4). This method reduces truncation errors, allowing for accurate depictions of flowlines with larger step sizes (Butcher, 2016). RK4 strikes a good balance between computational efficiency and accuracy. The process for creating the flowlines can be outlined as follows:

1. Calculate the structure tensor field, S, from the gradient vector field of the seismic image.
2. Define our seismic flow velocity field $V(x,y)$ as the eigenvector e_2 corresponding to the smallest eigenvalue λ_2 at each location.
3. Initialize the starting coordinate (x_n, y_n) for the flowlines by extracting traces with a fixed increment along the seismic section and picking the sample on a specific event type on the trace.
4. For each starting coordinate, integrate the flowline using the RK4 method with step size h.

For each step, calculate

$$k_1 = hv(x_n, y_n), \quad (7)$$

$$k_2 = hv\left(x_n + \frac{k_{1x}}{2}, y_n + \frac{k_{1y}}{2}\right), \quad (8)$$

$$k_3 = hv\left(x_n + \frac{k_{2x}}{2}, y_n + \frac{k_{2y}}{2}\right), \quad (9)$$

$$k_4 = hv(x_n + k_{3x}, y_n + k_{3y}). \quad (10)$$

Update positions

$$x_{n+1} = x_n + \frac{k_{1x} + 2k_{2x} + 2k_{3x} + k_{4x}}{6}, \quad (11)$$

$$y_{n+1} = y_n + \frac{k_{1y} + 2k_{2y} + 2k_{3y} + k_{4y}}{6}. \quad (12)$$

5. Repeat step 4 until (x_{n+1}, y_{n+1}) is outside the boundary of the seismic image.
6. Store the parametrized path of each flowline for further analysis.

The main steps of the flowline extraction workflow are illustrated in Figure 1, going from the seismic section (Figure 1a) to the flowline representation (Figure 1d).

Application and discussion

In the following sections, we will provide an overview of the developed workflows and address one of the key aspects of the flowlines that we believe contributes to their effectiveness with respect to identifying unconformities and sequence boundaries. We will also investigate how the number of seed points used to initialize the flowline integration impacts the accuracy and overall outcomes of the results.

Unconformity and sequence boundary extraction

Each flowline initialization simulates the path of an imaginary particle within a steady fluid velocity field (Figure 1d). The opacity of the paths reflects the frequency of overlaps, with higher opacity indicating more overlaps. These overlapping paths often correspond to major unconformities or sequence boundaries in a seismic section, as unconformities tend to truncate other surfaces, creating shared paths. To quantify this, we introduce the overlap score, a metric that measures how much a flowline overlaps with others, helping us identify those likely to represent unconformities or sequence boundaries.

However, relying solely on the overlap score poses challenges. While major unconformities or sequence boundaries typically score highest in highly truncated systems, internal reflections within these systems also produce high overlap scores. This can overshadow less truncated systems, where critical boundaries may be overlooked due to lower scores being eclipsed by those from more complex systems.

To resolve this, we propose a filtering workflow. First, we calculate the mean overlap score to emphasize the most significant sequence boundaries or unconformities. Next, we apply a sorting and filtering process to retain only the highest-scoring flowlines while excluding internal reflections that overlap based on a threshold. This method ensures accurate identification of unconformities across different systems in the seismic section, regardless of truncation levels and is outlined as follows:

1. Construct a heatmap matrix $H(x, y)$ by accumulating the number of times a flowline intersects the matrix at position (x_n, y_n).
2. Let $\mathcal{S} = \{s_1, s_2, ..., s_n\}$ represent the list of surfaces.
3. Let $O(s_i)$ represent the overlap score for surface s_i, which we define as the mean of the accumulated heatmap values along the surface:

$$O(s_i) = \frac{1}{|s_i|} \sum_{(x,y)\in s_i} H(x, y), \quad (13)$$

where $|s_i|$ is the length of s_i. 4) Sort the list of surfaces, $\mathcal{S}$, in descending order based on their overlap score $O(s_i)$. 5) Define the set $\mathcal{S}_{selected}$ to hold the selected surfaces, initialized as $\mathcal{S}_{selected} = \emptyset$. 6) For each surface s_i in the sorted list, add s_i to $\mathcal{S}_{selected}$ if the overlap $U(s_i, s_j)$ between s_i and surface $s_j \in \mathcal{S}_{selected}$ does not exceed the overlap threshold U_{th}:

$$S_{selected} = \{s_i \mid U(s_i, s_j) \leq U_{th} \forall s_j \in S_{selected}\}, \quad (14)$$

where $U(s_i, s_j)$ is defined as the fraction of overlapping points between the surfaces s_i and s_j, ranging from 0 to 1. 7) Continue the selection process until all valid surfaces have been added to $\mathcal{S}_{selected}$.

The sorting of the surfaces before filtering ensures that we retain the highest-scoring surface within a truncation complex of flowlines, which often corresponds to the major unconformities or the sequence boundaries within each system. The result of the method can be seen in Figure 2. We have plotted the seven highest-scoring surfaces in Figure 2a. These seem to coincide well with some of the expected sequence boundaries in the system. The 20 highest-scoring surfaces are shown in Figure 2b, superimposed on the seismic section.

Figure 1. Illustrating the main steps of the flowline extraction workflow. (a) The input seismic section from the F3 Netherlands block. (b) Estimated dip field based on the orientation of the minimum eigenvector, e_2, in the seismic section. (c) The sampling process of the starting

position of the flowlines. (d) The integrated flowlines for the seismic section were sampled on both peaks and troughs.

Figure 2. (a) The top seven scoring surfaces with respect to overlap score ordered from 1 to 7 superimposed on the seismic. (b) The top 20 highest-scoring surfaces using an overlap threshold of $U_{th} = 0.7$.

The behavior of the flowlines in relation to the seismic amplitudes reveals interesting implications for geologic interpretation. While not directly dependent on seismic amplitudes, flowlines are indirectly influenced by them through the differential dip field from which they are generated. This relationship manifests in a noteworthy tendency: the flowline paths seem to trend toward the zero crossings of the seismic signal, regardless of where they are initialized.

We believe this stems from the underlying principles of the method. By following the direction of the minimum gradient of the structure tensor, which summarizes local amplitude gradients, the flowlines naturally gravitate toward areas of least amplitude variation. These areas will typically be closer to the zero crossings in the seismic data. Figure 3 demonstrates this, showing flowlines initialized on peak amplitudes. It is evident that these flowlines frequently trace the zero crossings or follow closely around them. The benefit of this characteristic becomes clear when considering unconformities or sequence boundaries, which are often characterized by lateral amplitude changes due to abrupt shifts in deposition or erosion. The inclination of flowlines to follow zero crossings and the insensitivity to amplitude changes proves particularly advantageous in this context, as it enables the capture of subtle and complex changes associated with these features.

Figure 3. Illustrating the tendency of flowlines to trace the zero crossing or follow closely around them even when initialized on peaks. The flowlines are plotted in red.

Another critical factor in the flowline generation process is the number of seed points used to initiate the flowlines, as this can significantly impact the results. To achieve an accurate flowline representation of the seismic section, it is essential to generate a sufficient number of flowlines, ensuring they are sampled from across the entire image. For optimal accuracy, using all trace locations as seed points would be ideal, but this is computationally expensive, especially during downstream sorting and filtering tasks. Instead, we employ a fixed-size increment for selecting seed points, balancing accuracy with efficiency. The impact of this approach is shown in Figure 4, which demonstrates the results of integrating flowlines sampled at every 20th, 50th, and 100th trace (representing 6%, 3%, and 2% trace sampling, respectively). Larger, laterally extensive features like unconformities or sequence boundaries are reliably captured at all increments, while smaller features, such as internal sequence reflections, are more sensitive to the trace sampling frequency. These suggest that varying the seed increment based on the specific can be beneficial. A smaller increment provides better resolution for detailed facies mapping, while a larger increment is sufficient for capturing broader, regional unconformities, reducing computational time without compromising accuracy for major structures.

Figure 4. A section of 100 traces showing the effect of the trace sampling frequency (every 20th, 50th, or 100th trace). The lateral extensive seismic features are preserved in all realizations. However, the finer features such as the facies reflections require higher sampling density to be preserved.

Identifying stratigraphic sequences

One of the main advantages of working with seismic data in the flowline domain is its ability to preserve geologic relationships over long distances, capturing long-range geometric dependencies and regional context. This preservation helps in better understanding the geometry of seismic structures and makes it easier to group flowlines into geologic units using simple clustering methods. Each flowline is represented as a feature vector, allowing for effective classification and analysis of geologic structures. One way to do this is by using the coordinates along the flowline's path, which capture long-range geometric information in the data. The feature vector can be based on the x, y, or both the x and y coordinates along each flowline. Because flowlines can have different lengths, we extend (or pad) each flowline so that they all match the length of the longest one in the data set. Figure 5 shows how the flowlines are divided into eight clusters using K-means clustering, where only the y coordinate along each flowline is used as the feature in the feature vector. These clusters correspond closely with the expected stratigraphic sequences in the section. Once the seismic sequences are identified, the cluster boundaries can be used to extract the sequence boundaries.

Additionally, each identified seismic sequence can be further subdivided into subsequences. Each sequence is defined by the range between the uppermost and lowermost flowlines assigned to a specific cluster. All intermediate flowlines within this range can then be extracted and reclustered using K-means clustering. For example, Figure 6, shows the reclustering of the light blue sequence (fourth from the top) from Figure 5 into four distinct clusters. This reclustering enables more detailed analysis of the geologic variations within each sequence.

Figure 5. Visualization of the K-means clustered result of the extracted flowlines, segmented into eight distinct clusters, each represented by a different color. When coloring the flowlines based on their assigned cluster, we obtain stratigraphic sequences that closely correspond to expected stratigraphic units in the seismic section.

Figure 6. Visualization of further segmentation of the light blue (fourth from the top) in Figure 5 using K-means clustering, segmented into four distinct clusters.

Tracking conformable surfaces

A key aspect of seismic interpretation is tracking conformable surfaces, represented by continuous reflections. Flowlines excel at identifying unconformities by focusing on geometric structure and being relatively insensitive to amplitude variations. This insensitivity helps flowlines gravitate toward zero crossings, which effectively highlights unconformities regardless of lateral amplitude changes.

However, this same strength in tracking unconformities presents a challenge when attempting to follow conformable surfaces. To address this, we introduce an amplitude likeness metric, α, which is the relative difference between the amplitude values between two consecutive points along a flowline:

$$\alpha(i) = 1 - \frac{|A_i - A_{i-1}|}{|A_i| + |A_{i-1}|}. \quad (15)$$

This metric serves as a stop criterion for flowline integration, where the flowline stops if the amplitude likeness, α, falls below a certain threshold α_{th}. This ensures that each point added to the flowline does not differ significantly from the event type we aim to track. To improve flowline integration, we calculate a new differential dip field based solely on the specific event type we aim to track. For instance, if tracking peaks, we first mask out the troughs from the seismic image before deriving the dip field.

After extraction, we process the flowlines to create a single flowline per reflector, similar to unconformities. A well-tracked peak reflection should follow the maximum peak value and remain continuous. Our selection is based on two criteria: reflection length and amplitude. Our process begins by removing shorter flowlines when they overlap with longer ones, keeping the longest representation. We then sort the remaining flowlines by descending mean amplitude. Finally, overlapping sections are removed from lower-amplitude flowlines to preserve the highest-amplitude representations.

The result of this process is a set of flowlines that aim to represent each reflector in the seismic image. These flowlines are designed to follow peak values, maintain continuity along the reflection, and balance both length and amplitude considerations. Figure 7 illustrates the seismic section with conformable reflections tracked using our proposed method. The tracking was performed on the peak event with an amplitude likeness threshold of $\alpha_{th} = 0.3$. This example suggests that the flowline methodology can be used to reasonably track continuous reflections in the seismic data as parametrized line segments in 2D.

Figure 7. Illustrating the tracking of conformable surfaces by including the amplitude threshold, $\alpha_{th} = 0.3$, as a constraint for the flowline integration process.

Toward 3D

Transitioning from 2D to 3D flow analysis involves significant complexities due to the added dimension, introducing extra variables and more intricate interactions within the flow. This complexity increases the computational burden and challenges in numerical integration. While our current workflow is not sufficiently robust to be directly applied to 3D seismic surface identification, we aim to demonstrate the feasibility of extending it through a simplified pseudo-3D approach, which we term "2.5D." This method retains the fundamental aspects of 2D analysis while allowing us to extract unconformities in 3D. We regard a 3D surface as a collection of 2D flowlines that track the same structure in both the inline (IL) and crossline (XL) direction. We call this collection $\mathcal{S}$. First, we extract flowlines in 2D along an initial IL_n using the previously outlined unconformity extraction workflow and select the 2D surface we wish to track in 3D to form $\mathcal{S}$.

The points along surface, $\mathcal{S}_y$, are used as seed points for extracting flowlines in the crossline direction. We take a step Δ_{IL} in the inline direction and use the positions where the recently tracked crossline flowlines intersect $IL_n + \Delta_{IL}$. Each seed point in $IL_{n+\Delta IL}$ gives rise to a set of candidate flowlines, $\mathcal{C}_{n+\Delta IL}$. This step is crucial because the highest-scoring flowline regarding overlap between two inline slices does not necessarily correspond to the same surface. By initializing the starting seed points from our previous surface, we maintain the context of the 3D structure, maximizing continuity and coherence in the constructed surface. This approach helps to minimize misalignment and inaccuracies, especially in complex geologic formations. From the candidate flowlines, we select the flowline that achieves the highest overlap score in the heatmap calculated in $IL_{n+\Delta IL}$. This process is repeated for every inline, and the coordinates along the flowlines in $\mathcal{S}$ are written to file.

Figure 8 illustrates the surface obtained by extending an initial flowline using the 2.5D method. This surface was processed by importing the surface points into the OpenMind interpretation software, where basic postprocessing techniques, including smoothing and gap interpolation, were applied. This demonstrates that the proposed pseudo-3D method can produce a reasonable approximation of the expected stratigraphic surface in 3D.

The advantage of this method lies in its simplicity and efficiency, providing a practical approach for achieving a 3D extension from our initial 2D framework. However, one of the complexities inherent in this method is related to the variability in flowline tracking across separate 2D inline slices. There is no guarantee that the tracked flowlines in different slices will belong to the same surface even when using the seeding strategy proposed in our 2.5D method. The seeding strategy in our method only increases the likelihood that they will align closely enough to provide a coherent surface representation.

Despite this limitation, the pseudo-3D method offers valuable insights into the subsurface structure. While it does not capture the full complexity of the real 3D geology, the results are sufficient to enhance our understanding of stratigraphic relationships and the overall subsurface structure.

Figure 8. The 3D surface extended from a selected 2D flowline in the F3 Netherlands block. The flowline is initialized on $IL = 440$ and we employ a step size of $\Delta_{IL} = 5$. A vertical time shift of up to 10 samples is allowed between neighboring points. The surface is smoothed, and gaps are filled using OpenMind's interpretation workflows.

Application on different data sets

In this section, we will demonstrate the applications of the flowline workflow on two different examples. Both examples are taken from modern broadband 3D seismic data sets, covering the southern part of the Loppa High in the southwestern Barents Sea (Vinje et al., 2017). First, we demonstrate the extraction of first-order stratigraphic units in a relatively simple tectonic setting, followed by addressing the challenges that arise in more complex tectonic environments.

Example 1. The section in Figure 9a shows the part of the Loppa High that crosses the Alta discovery, showing a tilted basement block overlain by eastward-thickening stratigraphic sequences of Upper Permian and Lower Triassic age (Lie et al., 2018). To extract these stratigraphic sequences, we apply the previously described clustering workflow. Because our aim is to focus on the stratigraphic sequences, we minimize the influence of the tilted basement by initializing flow only from the seismic samples located above the basement and ensuring no flow extends into the basement.

After generating the flowline representation of the seismic data, we resample each flowline to match the length of the longest flowline in the data set, using the y-coordinates as features. Figure 9b displays the stratigraphic units identified through K-means clustering, initialized with six clusters, which seem to correspond reasonably well with the expected first-order stratigraphic units in the section.

Figure 9. (a) Seismic section over the Alta discovery in the southwestern Barents Sea. (b) The same section with K-means clustered flowlines superimposed, representing the first-order stratigraphic units.

Example 2. One of the primary challenges in working with flowline representation is dealing with faulting. Typically, we assume that the dip field aligns with the stratigraphy, allowing flowlines to follow continuous depositional patterns. However, when tectonic activity introduces faults, this assumption no longer holds, leading to arbitrary and erratic flowlines that fail to represent meaningful stratigraphic information. To address this challenge, a simple yet effective solution is to terminate flowlines at fault boundaries. This can be achieved by utilizing a fault likelihood volume (Hale, 2013), which identifies regions where faults are most likely to occur. By stopping flowlines at these boundaries, we ensure that they do not extend across fault planes, thus preventing distortions in the geologic interpretation.

While this method yields a more accurate representation of the seismic stratigraphy in the flowline domain, it has the drawback of losing lateral continuity across faulted strata, which limits the ability to maintain the regional context of the flowlines. We address this issue by using dynamic time warping to generate a correlation section, similar to the approach proposed by Bugge et al. (2019), allowing us to reestablish the lateral continuity of the flowlines across the faults.

Figure 10 presents the results of our workflow applied to a more tectonically complex setting, located farther west of the previous example. Both the flowline domain (Figure 10a) and the seismic section (Figure 10b) are shown. In both figures, the lowermost continuous flowline above the faulted reflectors is highlighted in red, with a set of reconnected flowlines superimposed. These reconnected flowlines align well with the faulted stratigraphy in Figure 10b, suggesting that our approach can be used to maintain the effectiveness of flowline representation even in complex stratigraphic settings.

Figure 10. A seismic section, showing a more complex tectonic setting from the southwestern Barents Sea. (a) The flowline representation of the seismic section, where the flowlines are terminated at fault boundaries. (b) The reconnected flowlines derived from our method are superimposed on (a) the flowline representation and on (b) the seismic section. The reconnected line is highlighted in red, with a set of reconnected flowlines aligned as the red line at the top.

Conclusions

In this study, we explored the potential of working with seismic images in the flowline domain, which offers several advantages for geologic interpretation by capturing long-range geometric dependencies and building regional context. Flowlines naturally converge near sequence boundaries and unconformities, facilitating their identification, ranking, and extraction based on overlap with other flowlines. This characteristic, combined with their insensitivity to amplitude variations, makes flowlines particularly effective for tracking unconformities or sequence boundaries, which often exhibit lateral changes in amplitude due to shifts in deposition or erosion.

The regional context provided by the flowline domain also lends itself well to machine learning applications, such as clustering, allowing for the efficient grouping of flowlines by similarity and the extraction of seismic sequences and subsequences. We also introduced a method for tracking conformable surfaces by using the relative amplitude change along the flowlines to steer their paths to better align with the conformable reflections.

While the extension of flowlines into 3D is still ongoing, our pseudo-3D approach shows promise for preliminary geologic analysis of well-defined surfaces.

Faulting remains a significant challenge in the flowline domain because following the dip in faulted areas often results in flowlines that do not align with the seismic stratigraphy. To resolve this, we terminate flowlines at fault boundaries using fault likelihood volumes. We then reconnect the terminated flowlines using dynamic time warping to restore regional context and lateral continuity across faults. This method shows that the flowline workflow can be effectively adapted for more tectonically complex geologic settings. TLE

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Data and materials availability

The code related to the open-source data set in this research will be made publicly available under an open-source licence at https://github.com/adelved/seismic-flow.

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References

Anderson, J. D. 1995, Computational fluid dynamics: The basics with applications: McGraw-Hill. Badley, M. E., 1985, Practical seismic interpretation: International Human Resources Development Corporation. Bahorich, M., and S. Farmer, 1995, 3-D seismic discontinuity for faults and stratigraphic features: The coherence cube: The Leading Edge, 14, no. 10, 1053–1058, https://doi.org/10.1190/1.1437077. Bakker, P., 2002, Image structure analysis for seismic interpretation: PhD thesis, Delft University of Technology, https://www.google.com/search?q=https://repository.tudelft.nl/islandora/object/uuid%253Af3f60507-5b08-43cb-a309-c3446c972395, accessed 19 March 2024. Barnes, A. E., 2000, Attributes for automating seismic facies analysis: 70th Annual International Meeting, SEG, Expanded Abstracts, 553–556, https://www.google.com/search?q=https://doi.org/10.1190/1.1816121. Bugge, A. J., J. E. Lie, A. K. Evensen, J. I. Faleide, and S. Clark, 2019, Automatic extraction of dislocated horizons from 3D seismic data using nonlocal trace matching: Geophysics, 84, no. 6, IM77–IM86, https://www.google.com/search?q=https://doi.org/10.1190/geo2019-0029.1. Butcher, J. C., 2016, Numerical methods for ordinary differential equations, third edition: Wiley. Chung, T. J., 2010, Computational fluid dynamics, second edition: Cambridge University Press. de Bruin, G., H. Ligtenberg, N. Hemstra, and K. Tingdahl, 2006, Synchronized sequence stratigraphic interpretation in the structural and chrono-stratigraphic (Wheeler transformed) domain: