Unsupervised characterisation technique based on the Correlation Integral approach for 3D seismic data interpretation.

Pavel Karmanov, Paresh Nath Singha Roy and Ramakrushna Reddy

Abstract

We introduce an unsupervised characterisation method based on the Correlation Integral approach for interpreting 3D seismic data. We derive two attributes from this approach: the scaling exponent and its second-order or double derivative. Initially, the scientists used the Correlation Integral method to cluster earthquakes in time and space. We have modified this approach and made it convenient for studying 2D and 3D volumes of seismic data in an automated way. We tested the updated algorithm in the offshore Parihaka 3D seismic survey from the Taranaki Basin in New Zealand. Later, we implemented it in the onshore Dibrugarh 3D seismic survey from the Assam-Arakan Basin in India. The experiments show that the scaling exponent identifies the geological features based on amplitude energy: high scaling exponent values are connected with low amplitudes and vice versa. The double derivative accentuates gradual changes in the scaling exponent values. The two attributes make it possible to detect gas chimneys, channels, progradation clinoforms, channels, the tops of the horizons and faults in particular conditions.

Introduction

For the first time, the term 'scaling exponent' was used by Grassberger and Procaccia (1983a, 1983b) to measure the strangeness of the attractors in solar time series. The scaling exponent was derived from the Correlation Integral equation. Goryainov et al. (1997) concluded that the continental Earth's crust could be fractal by nature, and fractality is its universal property. Scientists use the Correlation Integral method for studying earthquakes and clustering them in space and time (Chandriyan et al., 2022; Gupta et al., 2021; Roy and Padhi, 2007; Roy and Ram, 2006). This approach can also predict the potential roof fall in coal mines (Mondal et al., 2017; Mondal and Roy, 2019). Roy and Gupta (2015) invented 'FractalAnalyzer' – a graphical user interface based on MATLAB code for automated clustering earthquakes. Using this MATLAB code, Karmanov et al. (2021) applied the Correlation Integral method to study seismic data for the first time. The scaling exponent and its second-order derivative made it possible to detect seismic horizons, progradation clinoforms, zones below the bright spots, channels, etc. Later, Karmanov et al. (2024) improved the technique and made it automated, allowing the study of large amounts of seismic data.

Method

The scaling exponent measures directionality in uniformly or haphazardly spaced parameters (Grassberger and Procaccia, 1983a, 1983b). The attribute is based on the Correlation Integral equation (1):

$$C(m) = \frac{2}{X(X-1)} \sum_{j=1}^{X} \sum_{i=j+1}^{X} H(m - m_{ij}), \qquad (1)$$

where X is the number of pairs of digital values (amplitudes); m is the scaling range; m_{ij} is the scaling distance value between any two points of the cluster set; H is the Heaviside step function.

The scaling exponent (S) is connected with the Correlation Integral through the scaling range m (2):

$$C(m) \approx m^{S}. \qquad (2)$$

The second-order derivative (3) or the double derivative (D) we can derive from the scaling exponent (S):

$$D = \frac{(\partial S/\partial t)_2 - (\partial S/\partial t)_1}{t_2 - t_1}, \qquad (3)$$

Where $(\partial S/\partial t)_{2,1}$ are first-order derivatives for the points 2 and 1, respectively, and t is time.

We applied modifications to the workflow of Karmanov et al. (2021) to calculate the scaling exponent and its double derivative (Figure 1). The initial code could compute the attributes only for separate seismic traces. The computational process required multiple manual transfers from Microsoft Excel to MATLAB and vice versa, which required significant time and effort. In the updated algorithm, we combine results from the separate seismic traces and visualise them in one figure. The SEGY file reading, computation of the scaling exponent and its double derivative and visualisation occur automatically in one MATLAB code. We can study seismic data in 2D and 3D modes. The updated algorithm automatically allows the study of a significant amount of data in less time.

We improved two parameters in the MATLAB code: 'the trace interval' and 'the window length'. The term 'trace interval' signifies how frequently we collect seismic traces from the dataset for the computation. Karmanov et al. (2021) used trace interval 100. In our work, we reduced this parameter to 5. The term 'window length' identifies how many sequential amplitude values we collect from a seismic trace to compute one scaling exponent value. In the work of Karmanov et al. (2021), the window length was equal to 50. We decreased this parameter to 10. We selected the window length 10 because the total number of data points was limited; therefore, computations with lower values of the window length could not be stable. Choosing a window length larger than 10 caused increasing computational time and deterioration of the final data quality. This deterioration in the quality of the scaling exponent results occurred due to changes in the relation

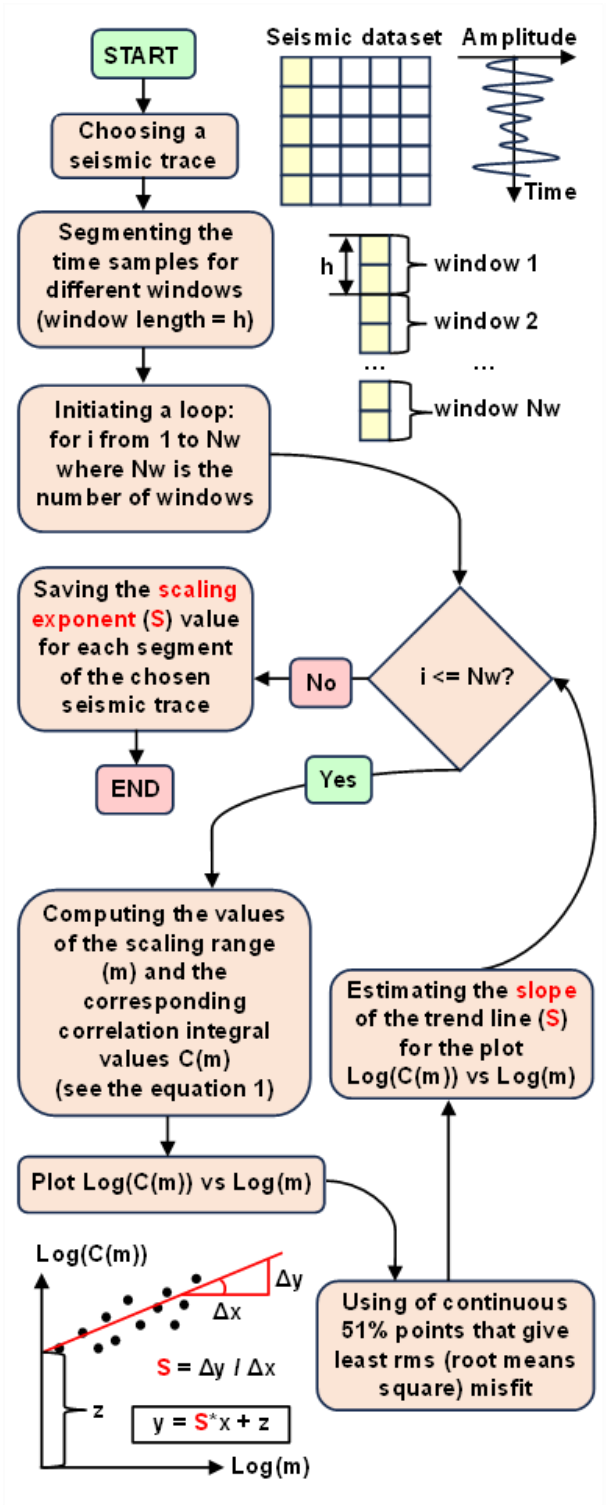

Figure 1. Graphical explanation of the scaling exponent computational process through the correlation integral. Modified after Karmanov et al. (2021).

between bigger and smaller scales. While increasing the window length, the link between scales changes towards bigger scales, and smaller features become less prominent. Such an effect causes blurring of the results images and decreasing resolution. After reducing the trace interval to 5 and the window length to 10, the final quality of the scaling exponent data significantly increased.

Initially, the quality of the Dibrugarh 3D seismic survey was insufficient. Therefore, we needed to apply some filtration techniques to increase the signal-to-noise ratio of the seismic data. We applied filtration attributes and tools available on OpendTect software for such purposes. Totally five filtration techniques were used: 1) Automatic Gain Control (AGC); 2) Frequency Filter; 3) GapDecon (Gap Deconvolution); 4) The averaging technique ('Demo: How we can fill in missing traces in OpendTect', 2019): 2 times; 5) Dip-Steered Median Filter (DSMF): 2 times. The application of the abovementioned techniques increased the quality of seismic data.

Examples

Parihaka 3D is an offshore seismic dataset from the Taranaki Basin, New Zealand. The survey has a fold equal to 60; the bin size is 6.25 m × 25 m, and the sampling interval is 2 ms. We have collected the results of the scaling exponent and the double derivative computation for the inline 2605 of the 3D seismic survey (Figures 2a, 2b and c). For the comparison, we computed three conventional seismic attributes for the same section: similarity (Figure 2d), textural dissimilarity (Figure 2e) and textural homogeneity (Figure 2f).

Dibrugarh 3D is an onshore seismic survey from the Assam-Arakan Basin, India. The survey has a 50 m × 25 m bin size, and the sampling interval is 4 ms. The signal-to-noise ratio remained low despite the use of filtration methods. Therefore, we accepted this situation as a possibility to test the performance of the scaling exponent and the double derivative in noise-contaminated seismic data. We computed the two attributes for the inline 710 of the Dibrugarh 3D seismic survey (Figure 3). We compared the results from the Correlation Integral attributes (Figures 3b and c) with the results from conventional seismic attributes: similarity (Figure 3d), textural dissimilarity (Figure 3e) and textural homogeneity (Figure 3f).

Results

For the Parihaka 3D seismic survey, the scaling exponent (Figure 2b) and the double derivative (Figure 2c) showed prominent performance in detecting the seismic horizons, the gas chimney, the progradation clinoform unit, and the gas chimney. However, they showed less prominent results in identifying the Cape Egmont Fault. The similarity attribute (Figure 2d) detects faults with high precision but faces problems with gas chimney identification. The textural dissimilarity (Figure 2e) and homogeneity (Figure 2f) depict both features: the Cape Egmont Fault Zone and gas chimneys.

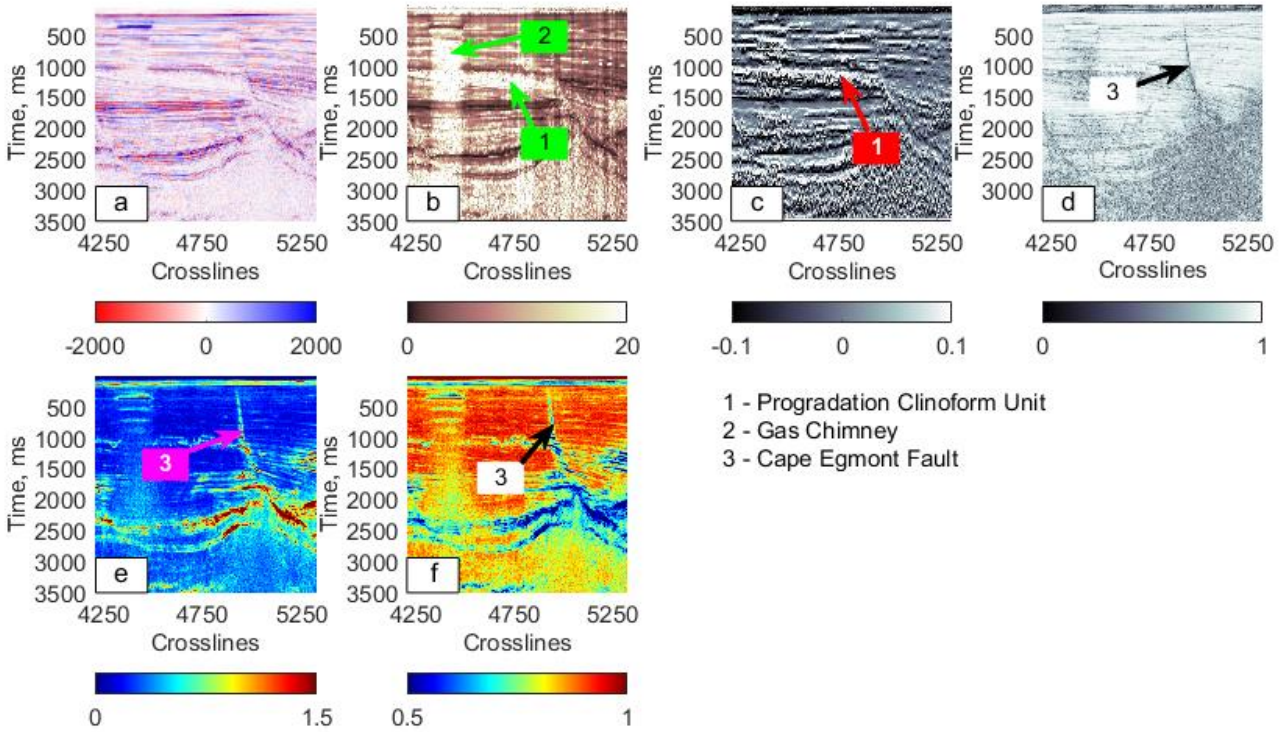

Figure 2. Parihaka 3D offshore seismic survey from the Taranaki Basin, New Zealand. Inline 2605. The seismic section (a), and a comparison between the scaling exponent (b), double derivative (c) and other conventional seismic attributes: similarity (d), textural dissimilarity (e) and textural homogeneity (f).

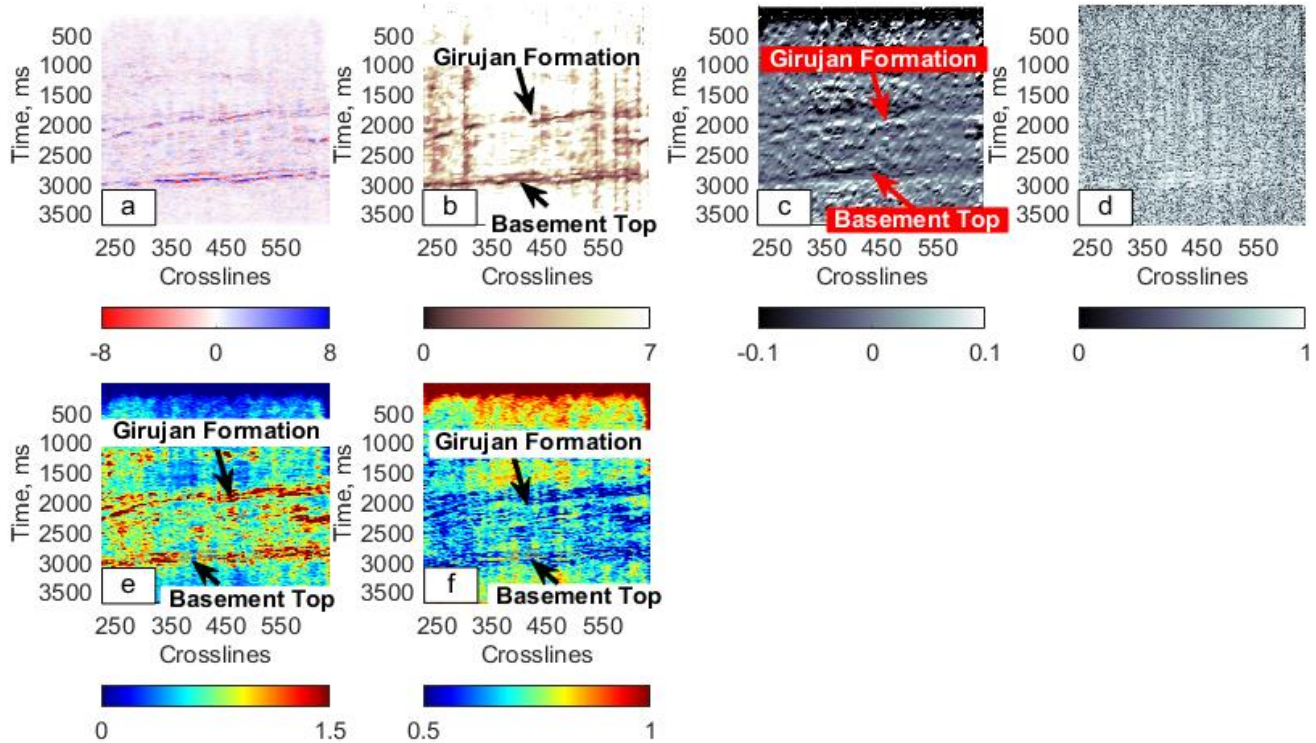

Figure 3. Dibrugarh 3D onshore seismic survey from the Assam-Arakan Basin, India. Inline 715. The seismic section (a), and a comparison between the scaling exponent (b), double derivative (c) and other conventional seismic attributes: similarity (d), textural dissimilarity (e) and textural homogeneity (f).

After the observations, we can conclude that the scaling exponent and the double derivative highlight objects that create amplitude contrast: high scaling exponent values are connected with low amplitudes and vice versa. The main criterion for the feature detection should be the amplitude contrast between the feature and the surrounding environment. Progradation clinoforms, channels, and gas chimneys create amplitude contrast with the environment; therefore, the scaling exponent can detect them. The scaling exponent can also detect the faults if the abovementioned condition is satisfied.

For the Dibrugarh 3D seismic survey, the scaling exponent (Figure 3b) and its double derivative (Figure 3c) accentuate the Girujan Formation and the top of the Basement. These horizons create high amplitudes and reflect as low zones with low scaling exponent values. Due to the low signal-to-noise ratio, the similarity attribute fails to detect anything (Figure 3d). The textural dissimilarity (Figure 3e) and homogeneity (Figure 3f) can delineate the tops of the formations but with a sensitive influence of noise compared to the scaling exponent. Therefore, the scaling exponent and its double derivative can show prominent results even in noise-contaminant seismic data.

Conclusions

We derived the scaling exponent and its double derivative as seismic attributes from the Correlation Integral approach to interpret sizeable seismic data volumes. The scaling exponent delineates features based on amplitude energy: high scaling exponent values are associated with low amplitudes and vice versa. The double derivative indicates rapid changes in the scaling exponent values. Both attributes have the potential to become useful in seismic data interpretation.

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