Accelerating exploration for hydrocarbons using a novel artificial intelligence to spot the outliers on 3D seismic

Antoine Thomas(1), Nabil Tnacheri(1), Sumeet Raina(2), Lalit Mattu(2), Lionel Lhommet(1).*
Affiliations: (1) Seisnetics, (2) Essem High-TECH PVT

antoine.thomas@seisnetics.com

Keywords

Artificial intelligence, seismic, interpretation, exploration, horizons, genetic algorithm

Abstract

The information extracted from seismic data often constitutes the base of subsurface models which are used to make decisions for further exploration, appraisal, and development activities. With the quest for India's energy security, the need to find new gas fields or optimize hydrocarbon production is becoming topical. The genetic algorithm used here is a powerful tool to segment, classify and display the waveform variability over large seismic volumes. In a record time, we extracted all surfaces and rapidly identified outliers using the fitness attribute. The fitness characterizes a change of reflector geometry and geological facies, two features which drew our attention on specific variations within this volume appearing to be fluid escape features. Considering amplitude variations, we highlighted possible gas accumulations requiring deeper investigations. Overall, this work was performed in less than 2 hours from processing to pre-interpretation. This tool is a great help to look for new fields quickly or revisit existing datasets looking for prospects adjacent to existing infrastructures.

Introduction

The information extracted from seismic data often constitutes the base of subsurface models which are used to make decisions for further exploration, appraisal, and development activities. With the quest for India's energy security, the need to find new gas fields or optimize hydrocarbon production is becoming topical. To that aim, new seismic data is often acquired, or old data revisited, with still limited time for analysis and interpretation. To help the geoscientists screen through large libraries and focus their attention on what matters, we will describe a new approach using a genetic algorithm (GA) to automatically extract information from the 3D seismic data in an unbiased manner and in record time and show how this approach can be used to accelerate and improve exploration and appraisal of gas fields.

Theory

The artificial intelligence system described below, is global, fully automatic, and unbiased: it only processes data, without any "a-priori" (Dirstein & Fallon, 2011). Several authors have revealed how they used this tool to improve velocity models (Rahaman et al., 2022) and find prospects (Sundara et al., 2022).

The extraction of geological features (e.g., horizons) from seismic data can be seen as a data segmentation problem where the objective is to split the whole into the most coherent parts (Figure 1).

- An individual is a location in the volume characterized by the neighboring seismic waveform (the chromosome). Each waveform is characterized by its own unique suite of attributes (i.e., location, amplitude value, neighbor trace shape, etc.),
- The population is the set of all the individuals in all the locations of the entire seismic volume,
- A sub-population is a group of individuals (a seismic horizon) that have the maximal genetic similarity (maximal waveform similarity).

The purpose of the GA is to mimic the genetic process of biological evolution based on the "survival of the fittest" principle applied to the seismic samples to produce the optimal "sub-populations" i.e. the horizons. The seismic volume is represented as a population of individuals that must be grouped into horizons throughout the process of the biological evolution. Therefore, at every generation:

- The selection - only the fittest: individuals and sub-populations that have the highest fitness (seismic similarity) are allowed to evolve. The selection is in favor of cohesion: it tends to bring together those seismic waveforms that constitute the most "balanced" horizons.
- The crossover: the selected individuals and sub-populations combine their genetic information to build a new generation. The combination tends to straighten the contribution of some seismic character and therefore to maximize the intra-sub-population similarity and maximize inter subpopulation dissimilarity.
- The evolution continues throughout the entire volume until all the sub-populations have been identified, characterized, and categorized into a database of horizons ready for analysis and interpretation.

The process is very robust and repeatable allowing the user to run in parallel several volumes and compare the number of surfaces extracted as well as their characteristics (amplitude, fitness, continuity…) as we will demonstrate in the following paragraphs.

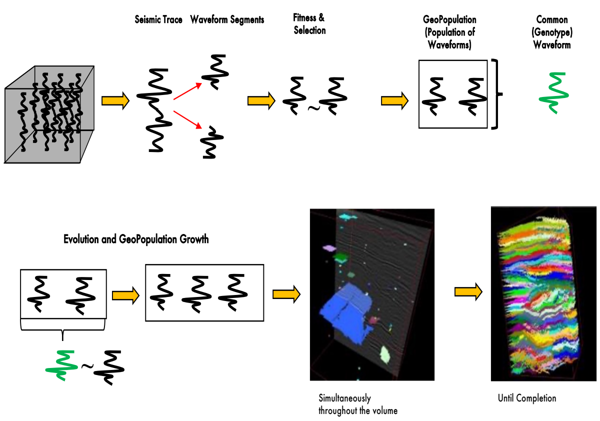

Figure 1: Principle behind the algorithm: waveform segmentation and evolutive classification using a genetic algorithm.

The suite of attributes examined included Two Way Time (TWT), Instantaneous Amplitude (Amp) and Fitness. The "Fitness" attribute provides a measure of "genetic likeness" for each member in the population when compared to the common waveform (genotype) of the same population (Figure 2). High fitness (green color) indicates a direct genetic relationship between an individual and the genotype. Lower fitness suggests a more distant relationship, like a 1st or 2nd cousin (blue and red color). Using the fitness attribute, it is possible to scroll through large 3D seismic volumes and look for outliers which would indicate a change of reflector geometry and geological facies, two features susceptible to draw the attention of the interpreter looking for outliers and possible hydrocarbon accumulations.

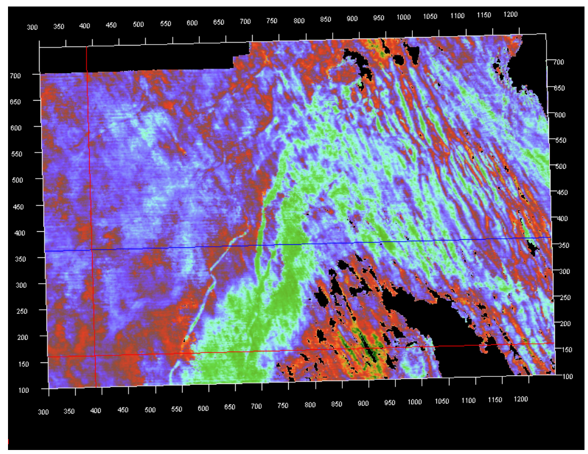

Figure 2: Example of fitness map showing a horizon extracted from the F3 dataset, offshore The Netherlands. The variability of seismic facies clearly reveals a complex meandering and the limit between an onshore environment on the right and an offshore environment on the left.

Case study and results

The case study is an offshore field in Northern Europe. The 3D seismic data was uploaded in the software without any pre-conditioning, no seed point or manual guidance. All surfaces were extracted in 27 minutes, allowing a quick scroll through the volume to identify outliers and zones of interest. Figures 2 & 3 shows the results of extraction with all horizons displayed in monochrome (Figure 3) and colored with the fitness attribute characterizing seismic facies variability (Figure 4).

Accelerating exploration for hydrocarbons using a novel artificial intelligence to spot the outliers on 3D seismic

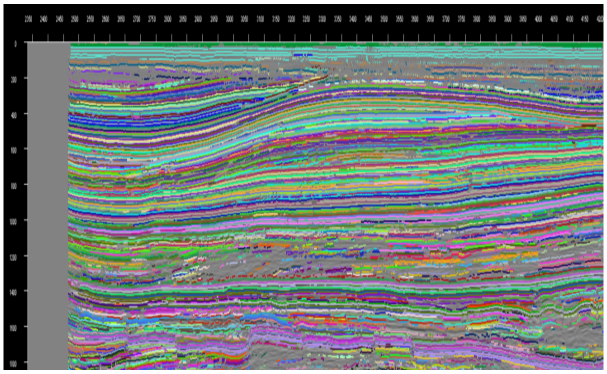

Figure 3: Surfaces extracted by the algorithm displayed in monochrome. Vertical scale from 0 to 1800 (TWT or depth), North on the right side. 50km from left to right.

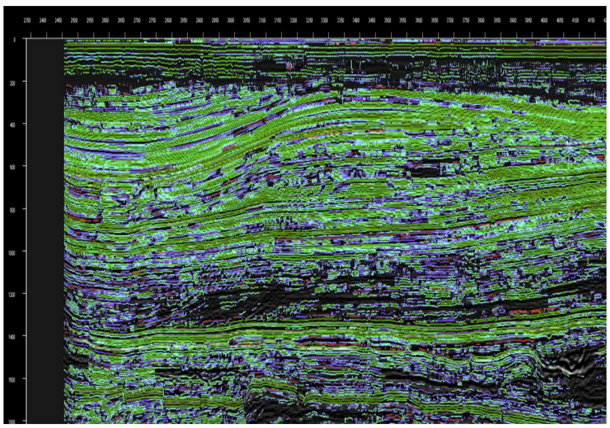

Figure 4: Display of surfaces using the fitness attribute. Green indicates high correlation between the waveform and the genotype for a single surface, blue and red highlight variability. Vertical scale from 0 to 1800 (TWT or depth). North on the right side. 50km from left to right.

A quick look at the fitness attribute can help spot the outliers requiring further investigations (Figure 5). Outliers typically shows in blue and red, red showing significant changes in seismic facies for the surface considered.

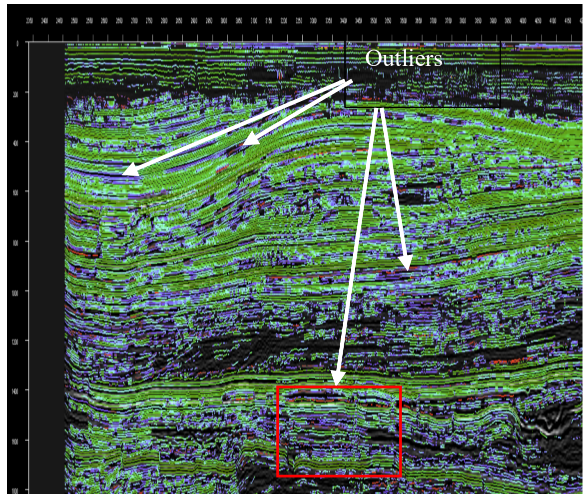

Figure 5: Spotting some outliers in the fitness display (blue/red). In the following paragraphs, we will zoom on the red rectangle. North on the right side.

As seen on the Figure 6, a series of reflectors are distorted and broken but still retain some internal seismic character. The fitness shows seismic waveform variations, changing from green to blue/red. The possibility to track such changes over a vertical section until their disappearance at the top (with a continuous horizon and little fitness change) suggests that these are fluid escape features.

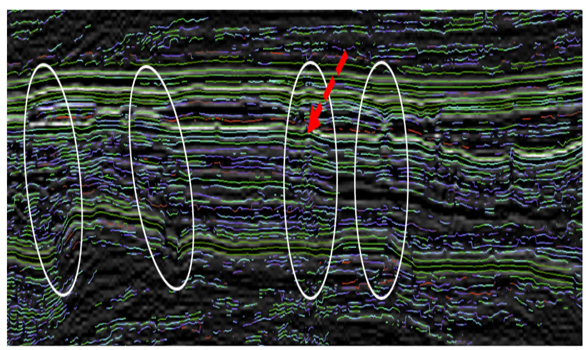

Figure 6: Zoom in the red rectangle highlighted in Figure 5. Cross-section view of an inline. The white circles show discontinuities in a series of horizons, with the fitness turning blue around these zones. These likely are fluid escape features warranting further investigations. The discontinuities stop at the top with a continuous and green surface showing

little fitness variability (cap rock). Vertical scale is 250ms, horizontal scale is below 10km.
By extracting and visualizing one surface pointed by the red arrow on Figure 6, we can clearly see on Figure 7 the geometry of the fluid escape features corresponding to the fitness color changes (blue and red). The green facies, quite homogeneous at first glance, will be analyzed later.

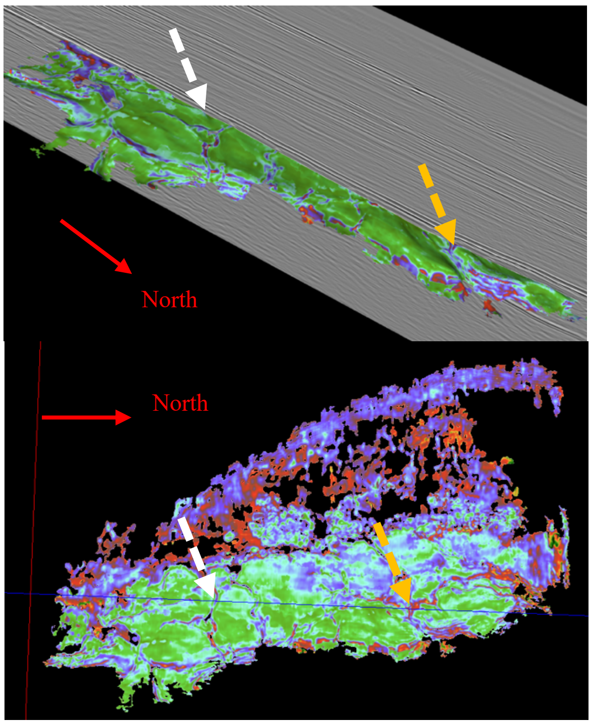

Figure 7: 3D side view (top) and top view (bottom) of a surface showing the variability of the fitness attribute. A series of green pockets are delineated by blue/red curvilinear fluid escape features (examples with the white and orange arrows pointing at these features for both views)

By displaying the amplitude attribute for the surface, we can observe large variations over the surface (Figure 8). The blue color corresponds to low amplitude values (3 to 100), while red peaks at 20,000. The lower values match with fitness breaks likely corresponding to the fluid escape features, while red could correspond to trapped gas.

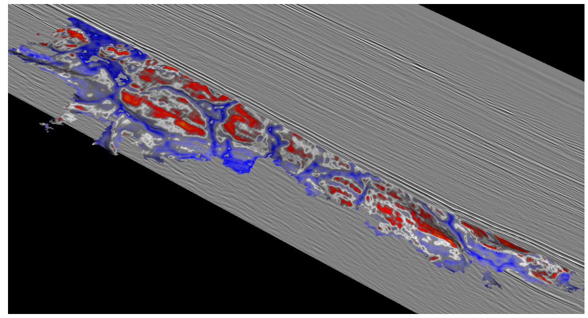
Figure 8 Amplitude variations over the surface with low amplitude in blue (value of 3) to high amplitude in red (values above 15000) The fluid escape features show low amplitude (blue). Red/greyish colors show high amplitude and could correspond to trapped gas in this horizon, and therefore a possible prospect.

Conclusions
The genetic algorithm used here is a powerful tool to segment, classify and display the waveform variability over large seismic volumes. In a record time, we extracted all surfaces and rapidly identified outliers using the fitness attribute. The fitness characterizes a change of reflector geometry and geological facies, two features which drew our attention on specific variations within this volume appearing to be fluid escape features. Considering amplitude variations, we highlighted possible gas accumulations requiring deeper investigations. Overall, this work was performed in less than 2 hours from processing to pre-interpretation. This tool is a great help to look for new fields quickly or revisit existing datasets looking for prospects adjacent to existing infrastructures.

References
Dirstein J.K., Fallon G.N., 2011. Automated interpretation of 3D seismic data using genetic algorithms. Preview, 2011:151, 30-37. doi: 10.1071/PVv2011n151p30.

Sundara S., Patnana R., Acharya B., Chawla V., Chitti S., Malla S., Kumar (2022). AI based and conventional seismic techniques for reservoir characterization of K-

IX and K-VIII pay sands in Nardipur Low area, Limbodra field, Ahmedabad sector, Cambay Basin, Gujarat. Conference: 5th South Asian Geosciences

Accelerating exploration for hydrocarbons using a novel artificial intelligence to spot the outliers on 3D seismic

Conference and Exhibition, GEO India (14-16 October, 2022), Jaipur, Rajasthan, India.

Rahaman A., Kumar A., Singh S. K.,, Akhileshwar P., Robust Low Frequency Model is the key to improve the accuracy of Pre-stack Inversion results: Case study from Contai, Bengal Basin, India. Conference: 5th South Asian Geosciences Conference and Exhibition, GEO India (14-16 October 2022), Jaipur, Rajasthan, India.