Introduction

A typical geoscience project is a sequence of actions for a detailed study of the field through an integral analysis of geological and geophysical information. The aim of this work is to minimize the geological risks of well drilling and increase the reliability of the geological prediction, as well as localize reserves and update their quality.

In the cycle of exploration project, stages that have a significant impact on the information content and detail of the result are identified:

- Well section correlation by stratigraphy intervals matching reservoir development stages: this stage results influence the filtration models quality and the reserves estimation correctness;
- Seismic horizons interpretation with fault model considered: the results of this stage determine model structural framework and make up the basis for subsequent dynamic wavefield analysis;
- Facies modeling accounting sedimentation environment.

Today, there are a large number of analytical approaches and algorithmic implementations for solving the problems of the above stages. Most of them have limitations due to the inability to fully automate processes when working in the complex geological environment, as well as with poor quality material. The authors of this paper have found a solution of these problems in related areas. At this moment, one of the top areas to gain scientific attention is theory of computer vision. Computer vision technologies are developing more and more actively in various fields and areas. A set of solutions is proposed in the work, based on attracting the capabilities of AI to solve the problems of automating the processes for tracking seismic horizons and faults, correlation of well sections, facies modeling.

Automatic well sections correlation

Key challenge here is to propose a solution that correctly fits the purpose to account complex stratigraphy and can handle massive loads of data including some questionable quality data sections. In order to automate the well section correlation process, there is also an algorithm proposed that works on basis of a convolutional neural network consisting (CNN) of encoder and decoder, both including five one-dimensional convolutional layers (Brazell S. et al. 2019). When training the neural network, at first, there is a feature vector as encoder output. Then it goes to the decoder input, and finally, the decoder outputs a restored curve. This algorithm inputs a set of log curves for neural network training and well coordinates where automatic correlation is performed. In this case, you do not need any well tops initially for correlation, since the control points on tracks selected automatically during operation. The correspondence between the automatically determined control points for a pair of traces is sought in the feature space.

The algorithm result is shown on Figure 1.

![Figure 1. Autocorrelation results using a neural network algorithm for the GR curve (GridPoint Dynamics LLC)](image-url)
The advantage of CNN algorithm applied in this work over standard approaches is the automatic determination of control points for correlation.

**Seismic horizons tracking and faults detection**

When interpreter starts handling big volumes of input data, especially of complex geology, it is necessary to have some tools that allow quick estimation of area’s key structural peculiarities.

The technology uses a multilayer U-net architecture CNN, which consists of an encoder and a decoder connected by bypasses. As an encoder, the ResNet50 model trained on a set of synthetic data is used. CNN (Li S. et al. 2019) trained on such a set of model data, is able to take into account a large number of wavefield features: low quality of input data, near-surface zone anomalies, fold loss zones, various processing “artifacts”, complex seismic structures, and faults different by amplitude, length, and genesis.

When using this approach for seismic horizon autocorrelation, it is suggested to move away from working with traditional seismic sections to predicting local geological time (LGT) sections from seismic images. These sections are color-coded images, where a single color segment assigned to highlighted reflection by comparing its amplitude and shape on adjacent paths. The result is the allocation of contours corresponding to the horizons on the predicted LGT. Worth mentioning advantages of this approach are the possibility to simultaneous trace of a series of reflecting horizons and detailed fault zones incorporation, and to keep results robust regardless of input data quality.

Figure 2 represents model data preparation for training and the result of predicting the LGT section after training the neural network, as well as the result of autotracking algorithm applied on a real seismic data section.

![Figure 2. Seismic horizon autotracking: neural network training and the result of the algorithm (GridPoint Dynamics LLC)](image-url)
The problem of determining faults is solved in a slightly different way and is transferred to computer vision as a segmentation of 3D seismic images. Segmentation is the partitioning of an image into many areas covering it (Wu X. et al. 2019). In the presented method, image segmentation also performed as CNN. At each point in the input seismic volume, the neural network learns to put one where there is a fault and zero where there is not.

Practical implementation of approach described above is to calculate the fault probability volume, that consists of indexes from 0 to 1, which is a self-sufficient result of applying an artificial intelligence. However, the main advantage of the proposed technology is the option to perform fine-tuning on the neural network manually for each specific project, region, and fault type. To retrain the network, additional manual marking of fault sticks at 1-10 cube sections is required, depending on the complexity of the material. The result of the marked sections is extrapolated to the entire cube, the neural network adapts to new data and the result of the prediction improves.

Figure 3 shows comparison of seismic sections in transparent mode with blended input seismic volume with amplitude data and probability volume, obtained in two options: without retraining (A), network retrained on 5 sections (B), network retrained on 10 sections (C).

**Figure 3. Fault autotracking: comparing options for calculating probability volumes (GridPoint Dynamics LLC)**

Above-mentioned techniques enable fast structural interpretation workflow, given appropriate network training. AI-based methods provide specialist with robust result with almost no need in cleaning thousands of tiny fault patches or propagate horizons with dozens of opaque tuning iterations.

**Cognitive facies model construction**

The traditional approaches to facies environment, observed by Jayaram V. et al. 2015, suggest the usage of various input data and provide variable accuracy of facies maps and volumes. Many of them don’t match a geological task when applied under certain subsurface settings.

When constructing maps, the classification methods are based on the idea of classifying well logs and seismic traces according to their shape. To build volumetric models, clustering algorithms are applied to each point of the cube under study and, in addition to the initial seismic data, use seismic attributes. Geophysical data can be used as a training set for machine learning algorithms with a teacher. In this case, the identified facies based on the well log or log interpretation data, which significantly increases the value of the results obtained. In addition to facies models, these approaches can be used to predict any discrete or continuous parameters in the inter-well space, as well as to conduct a probabilistic assessment of their distribution forecast.
Figure 4 presents the results of the operation of the algorithm for predicting lithology values in the inter-well space.

![Figure 4](image)

**Figure 4.** The results of building the facies cubes (GridPoint Dynamics LLC)

The presented ideas can greatly simplify and accelerate the work of geologists, reduce the share of subjectivity of the results.

**Conclusions**

In the current conditions of starting development of more and more complex oil and gas fields, both in terms of geological structure and reservoir fluids, the issue of optimizing and improving geoscience project teams work quality is significantly relevant.

New approaches described in this article based on artificial intelligence make it possible to develop the automation of more and more operations, providing an additional effect with both accuracy and level of detail increased. Once applied, the comprehensive set of solution presented, will allow geologist to bypass a huge group of problems and restrictions that are still actual roadblocks.

**References**


