Introduction

West of Shetland (WoS) area is located offshore NW Scotland on the SE margin of the Atlantic Ocean and comprises numerous sub-basins and intra-basin highs that are host to several significant hydrocarbon discoveries (Fig. 1). But less than 200 exploration wells have been drilled WoS in the last 40 years, this area is a frontier area. After analysis of exploration technical challenge in this area, it was highlighted that most failed wells were drilled on poorly defined or invalid traps and on prospects that lacked reservoir or poor top seal (Loizou, 2008). Mis-interpretation of high-amplitude features has contributed to the failure of several wells. These exploration technical issues can be related to seismic processing and imaging problems from the past exploration activities.

![General structure map of West of Shetland area (Loizou et al., 2008)](image)

In last 30 years Kirchhoff migration has been dominated for seismic imaging, but it has some limitations like multi-ray path calculation and complex structure area imaging (Etgen et al., 2009). For de-risking the WoS exploration new Angle domain pre-stack depth migration algorithm Generalized Radon Transform (GRT) has been applied to preserve true amplitude and output exact angle gathers which are two important factors for Reservoir Characterization. GRT is ray-based migration scheme but it carried out in angle domain. The detailed method will be discussed in the next section.

Machine Learning methods have been applied into different industries in recent years. For oil and gas exploration machine learning methods can be integrated to improve efficiency, decrease uncertainty and de-risk exploration. Different authors have integrated machine learning into Seismic Interpretation workflow, like salt body boundary detection, horizon and fault interpretation. Laura et al. (2018) provided using machine learning clustering algorithm to pick AVO anomaly area. After the target area has been chosen the detailed seismic attributes analysis is needed for reservoir study. Principal component analysis (PCA) and Self-organizing map (SOM) unsupervised machine learning methods applied by Roden et al. (2015) in seismic attributes analysis can quickly pick the details of the reservoir. Here those two unsupervised machine learning methods will be integrated into QI workflow and applied on WoS seismic dataset.

Methods and Workflow

Problem Statement:
To overcome the amplitude ambiguity generated by Kirchhoff imaging techniques and to de-risk the exploration targets using combined techniques of angle domain imaging and machine learning on some of the old 1990-2000 acquired data.

Solution:
1. GRT Angle domain Pre-Stack Depth Imaging

Generalized Radon Transform (GRT) migration is a 3D angle domain migration based on the theory of generalized Radon transform (GRT) for massively parallel commodity clusters (Ettrich et al.,
The migration algorithm is a true-amplitude migration based on ray tracing that computes the reflection response in dependence on sub-surface angle of incidence:

$$R(\theta, \psi, x) = \int \mathcal{W} \left[ x^f, T(x^f, x, x^s), x^s; x \right] d\mathcal{V}^m \text{ with } \mathcal{W} = \frac{|p_n(x)|^2}{2V^f(x) \cos \alpha^f V^2(x) \cos \alpha^s}$$

where $\theta$ is the inclination angle of the incident ray, measured with respect to the vertical direction, and $\Psi$ is the azimuthal angle. For narrow azimuth data, the azimuthal component is sparsely covered and the migration result $R(\theta, x)$ is computed solely in dependence on the inclination angle at sub-surface points $x$. Seismic input traces $u$ should not have any amplitude scaling applied prior to GRT migration. GRT internally converts the input traces to versions $u$ from which the amplitudes are picked according to computed traveltimes $T(x^f, x, x^s)$ between source / receiver and output point $x^f, x, x^s$. The weighting factor $W$ and integration weights according to the dip-vector increment $d\mathcal{V}$ make the output $R$ proportional to the reflection coefficient.

2. Machine learning and AI

After high quality angle gathers have been created using 3D GRT migration, AVO anomaly analysis needs to be applied on the gathers to find potential target area. Unsupervised machine learning methods like clustering which is generally used to recognize patterns in the data can be integrated and applied on the seismic gather datasets. Fuzzy c-means clustering is a method of clustering allows one piece of data to belong to two or more clusters. The outputs after clustering will be labelled cluster volumes and probability of cluster membership volume for each cluster. The general workflow is in the below:

![Figure 2. General workflow of Fuzzy c-means clustering on seismic angle gathers.](image)

The input data is instantaneous amplitude of every subsurface sample on each angle trace at target horizon. Number of clusters can be pre-defined after quickly scanning through angle gathers of a few inlines and xlines. Outputs include cluster volumes of different clusters and for each cluster a volume is generated that indicates the degree of membership of every subsurface sample to each cluster.

Potential target area can be quickly picked up using Fuzzy c-means clustering, next step will be detailed seismic attributes analysis in the focused area. Nowadays, there are so many seismic attributes available in different software. How effectively the analysis can be done? Unsupervised machine learning methods Principal component analysis (PCA) and Self-organizing map (SOM) can be applied to solve the problem. PCA is a linear mathematical technique used to reduce a large set of seismic attributes to a small set that still contains most of the variation in the large set (Roden et al., 2015). Using PCA the most contributed seismic attributes can be picked up from dozens of attributes for next step SOM. The self-organizing map (SOM) is a non-linear approach reduces the dimensions of data using unsupervised neural networks. SOM reduces dimensions by producing a 2D map that plots the similarities of the data by grouping similar data item together. The schematic workflow is shown in the below:
Figure 3. Schematic workflow of PCA and SOM.

Input data are multi-seismic attributes, after PCA some most contributed attributes left for SOM. Final output will be SOM 2D section or map display.

Examples

After high quality angle gathers (see Fig.4) have been generated through GRT migration, near, mid and far angle stack volumes are created. Following general QI workflow coloured inversion has been done on near and far angle stack volumes, Extended Elastic Impedance (EEI) fluid (+20°) volume is calculated. Potential target horizon (T31) EEI fluid slice is shown in Figure 5 (Middle). Meanwhile, Fuzzy c-means clustering has been applied directly on the angle gathers. From Fluid replacement modelling and synthetics analysis on one of the dry wells in the area, for brine case amplitude of top reservoir increases a bit at far offset. For oil/gas cases, AVO anomaly at top reservoir can be considered as class II/III. One cluster which matches with AVO class II/III has been plotted in Figure 5, one real angle gather has been chosen on the cluster map for gradient analysis. The AVO anomaly at target horizon on the gather shows class II/III. The overlay slice map shows AVO cluster map from machine learning match with EEI fluid slice very well that increase our confidence on fluid distribution area for further reservoir study.

Figure 4. Pre-Stack Imaged Gather examples (left is GRT gathers and right is Kirchhoff gathers).

Figure 5 The Left image shows machine learning scanned AVO class II/III cluster at target horizon and one real angle gather gradient analysis. In the middle is EEI fluid slice at target horizon and on the right shows overlay the cluster map (blue points) and EEI fluid slice.
14 different conventional seismic attributes have been generated for potential target area like amplitude, envelope and Intercept etc. After PCA 8 largest contributed attributes have been chosen for SOM. A couple of 2D SOM sections are displayed in the below for analysis.

![SOM Section](image1)

**Figure 6** The Left image shows EEI fluid section (upper) and SOM section (down) of one inline which goes through potential fluid area. The line location is on the right corner of EEI fluid section. The Right image shows EEI fluid and SOM sections of another inline goes through a dry well. The line location is on the left corner of EEI fluid section.

From the upper left image of figure 6 we can clearly see fluid anomaly area on the EEI fluid section, the line location and fluid anomaly area show on the slice at the upper right corner. But we cannot see the details of the reservoir on EEI fluid section. When we investigate the SOM section in the below, there is a special pattern matches with fluid anomaly on EEI fluid section but in more details. The SOM section is calculated in a 100ms window above and below target horizon. On the Right is another line goes through one dry well, we can see there is no anomaly on EEI fluid section. The SOM section does not show a special pattern either.

**Conclusions**

For de-risking WoS area exploration GRT angle migration has been applied to preserve true amplitudes and provide high-quality angle gather directly through migration process. Machine learning methods like Fuzzy c-means clustering enables to quickly scan seismic angle gathers from large area and find AVO anomaly area for further study. PCA and SOM unsupervised machine learning methods provide more accurately exploration targets after choosing and combining different seismic attributes through the algorithms. The integrated depth imaging and QI machine learning workflow is proven to identify and de-risk exploration targets in the West of Shetlands in a time- and cost-efficient manner, whilst generating a high-quality seismic image and associated fluid attributes.

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**References**


