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Neural-network based multi-azimuth processing

A. Huck[1*], P. de Groot[1], T. Manning[2], W. Rietveld[2]

[1] dGB Earth Sciences, Enschede, The Netherlands
[2] BP Exploration Operating Company Ltd, Middlesex, United Kingdom
* Corresponding author; E-mail: arnaud.huck@dgbes.com

Summary
This paper describes the results of a series of experiments with neural networks, dip-steered noise reduction filters and other techniques aimed at combining multi-azimuth data.

The seismic data was first pre-processed by applying dip-steered noise reduction filters, amplitude correction and inter-volume trace matching for dynamic shift corrections. Then the individual azimuthal stacks were combined using first unsupervised - and then supervised neural networks using custom-made semi-automated workflows.

The main conclusions drawn from this study are that incremental improvements were achieved after consecutively: aligning the azimuth volumes, unsupervised stacking and supervised stacking. Alignment proved to be a mandatory step. Unsupervised segmentation provided a useful segment volume that highlights the area affected by stacking issues, while the same segmentation was also used for re-stacking the seismic data. Main improvements were achieved by selecting the relative weight to use for stacking. Supervised neural network stacking were further used to smoothen the transition between segment. The “MLP weighted” output is considered better than the input mazstack. The “MLP weighted” stack is perfectly fit for interpretation since no processing related artifacts were accepted. The workflow was adapted to the pre-stack domain but no additional gains were obtained.

Introduction

The Polaris Field in the West Med Deepwater concession of the West Nile Delta had Multi-Azimuth (MAZ) seismic data shot over it in 2006 by BP and it's partner RWE-Dea. MAZ acquisition and processing has been successfully implemented during recent years to optimize the quality of seismic data in complex areas. The Polaris Field is an example that shows how shallow and deep heterogeneities cause illumination problems for the deeper targets.

Each narrow azimuth towed streamer (NATS) acquisition pass forms an independent, well sampled, single azimuthal stack. MAZ surveys typically divide the azimuth space into 3, 4 or 6 bearings. The quality of these stacks varies spatially, in a way that no single azimuthal stack can be declared as the best. Manning et al (2007) showed that several stacking methods can be applied to generate a multi-azimuth stack (mazstack) which is generally better than the individual stacks. This paper proposes an improved workflow for the stacking of azimuthal stacks using artificial neural networks (Aminzadeh et al, 2004).

The work was conducted on a pre-stack depth migrated multi-azimuth survey, covering a 270 km^2 area (Manning and Baptiste 2008). Five of the six stacks were available from 0 (N/S) to 120 degrees with a step of 30. The depth migration was done using a single velocity model that had been built with a lot of care, down to and including the Messinian unconformity at about 3km. The Neural Network workflow presented here has been designed and used on post-stack data, but then adapted for pre-stack processing.

Data preparation

Several steps of data preparation were needed before the azimuthal stacks could be compared. First, an amplitude correction was applied to compensate for the loss of amplitudes with depth (see figure 1 before and after). This was performed using a power law function as a function of depth. The raw amplitudes were multiplied by the depth (in meters) to the power of 1.25. The amplitudes were further re-scaled to the original amplitude range by dividing them with a constant.

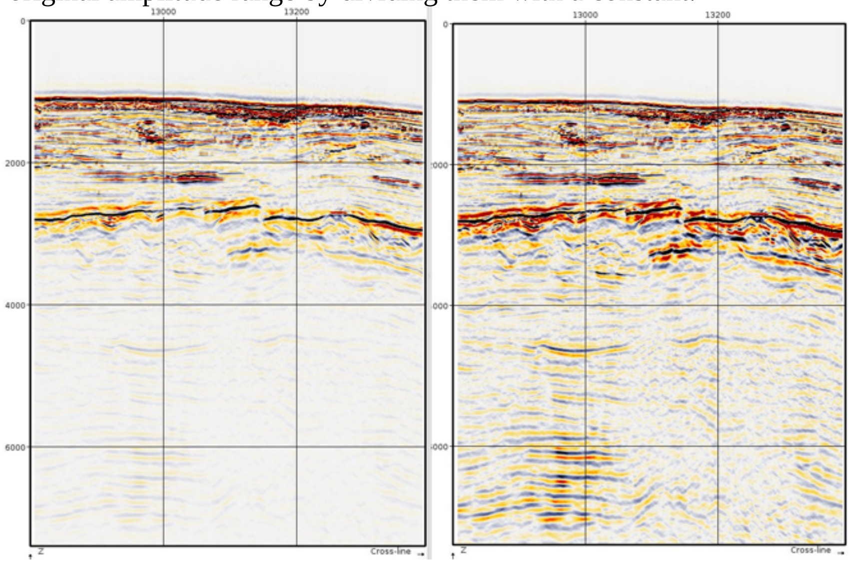

Figure 1 *Mazstack = sum of the 5 input stacks before (left) and after (right) amplitude corrections.*

Then a mild dip-steered median filtering was applied to remove some lateral noise. The dip field used to steer the filter was extracted from the sum of the 5 re-scaled stacks, hereafter referred to as the mazstack. No processing was applied on any mazstack itself - the mazstack was updated after each processing step by stacking the processed mono-azimuth stacks. The extracted dip field contains the inline and crossline dip attributes extracted at every sample location. However the level of accuracy of the extracted dip field is too high and must be decreased before structure-oriented filtering. Therefore a non-steered median filter with a stepout of 5 traces was applied on the raw detailed steering cube. The output "background" steering cube highlights the regional dip trends instead of the local displacements. It was used together with the seismic data to dip-steer median filter the seismic. A mild radius of 2 traces was used in order to remove the non-coherent lateral noise and also to preserve the actual lateral variations.

The seismic events in the five stacks showed some degree of misalignment, despite depth migration. This may be the result of using an isotropic velocity model or which vary with azimuth or more likely a reflection of the residual velocity error in the model due to the rapid lateral velocity contrasts in the Messinian which are not fully inverted for by the multi-azimuth tomography.

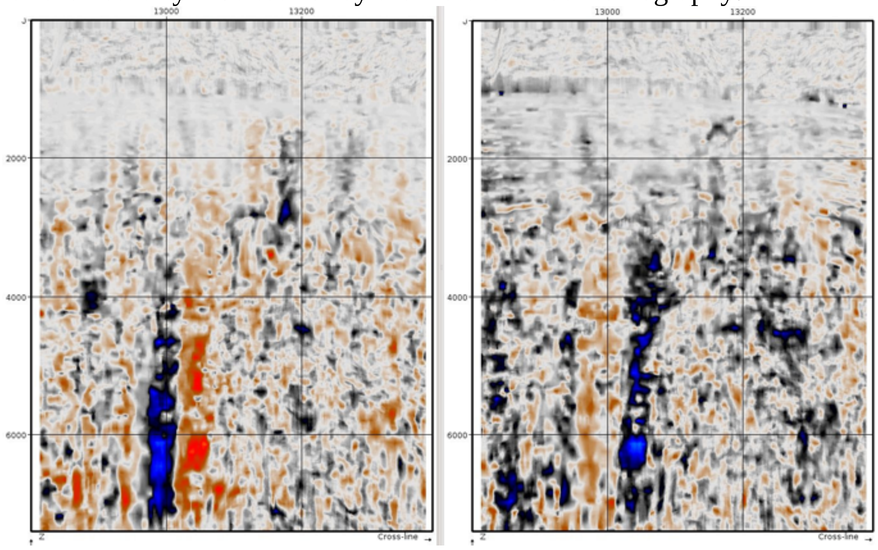

Figure 2 *Mazstack = Extracted shift fields at 0 (left) and 90 (right) degrees azimuth, from 30 meters up (blue) to 30 meters down (red).*

The following three-step flow was used to align the stacks. First the misalignments were quantified by tracking the strong events of each azimuthal stack w.r.t. a reference dataset, the scaled and filtered mazstack. The tracking was guided by a search window. This matching procedure returned a series of depth differences along a skeleton formed by the strong events. A vertical interpolation provided depth-shifts at every sample position. As the lateral continuity of the extracted shifts could be problematic, a dip-steered median filter with a large stepout was applied to the 5 shifts volumes (figure 2). The scale of the filtered shifts is then pseudo-3D. Finally the filtered shifts were applied to the individual stacks by warping the image.

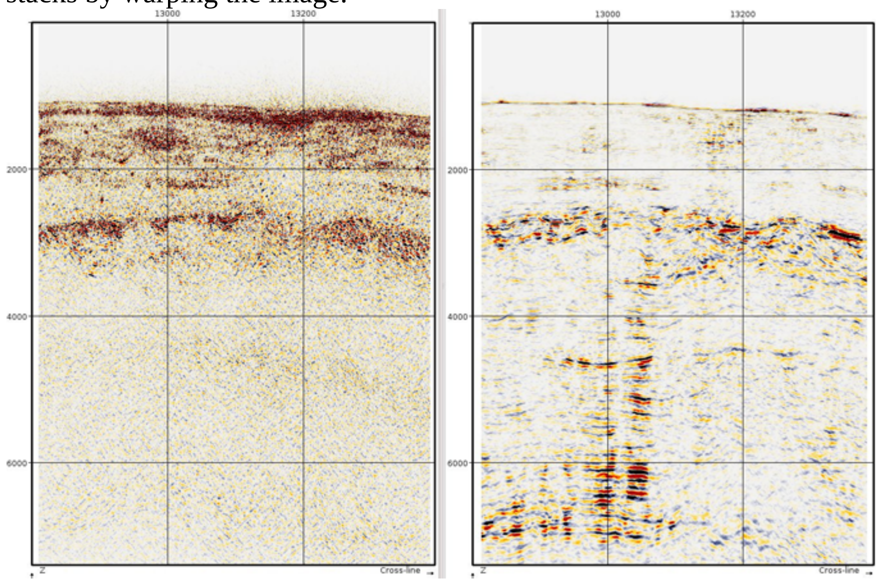

Figure 3 *Data QC: Difference (after-before) processing in mazstack because of structure-oriented filtering (left) and alignment (right).The colour scale is 10% of the original seismic scale.*

Figure 3 summarizes the gains of the data preparation phase: Structure-oriented filtering removed a large part of non coherent noise, while the alignment helped especially the deep (sub-Messinian) reflectors to be in phase for the next step.

Neural network stacking

Multi-azimuth stacking has been applied previously (Manning et al 2007, Manning et al 2008) by looking for the best individual stacks and weighting them in the stack. An alternative non-linear approach will use neural networks to automatically recognise the number and identity of the individual stacks that should be used to create the mazstack, as a function of space. Unsupervised Vector Quantizers are the appropriate kind of neural network to meet that purpose. They do not need a priori knowledge and can return spatially variable weights. Inputs are 3D local attributes that are able to quantify the quality of each individual stack. Inter-volume similarities were created for this purpose. They are a normalized cross-correlation between individual stacks and the reference mazstack. Since their amplitude varies between 0 and 1 (perfect match) they represent proper weight functions.

Five similarity attributes (one for each stack) were extracted on a random subset of the data, and classified during neural network training into a user-defined number of classes (10 for instance). The task of the neural network training is to find 10 vectors of similarities that will fit the data. The training is stopped manually when the misfit between the vectors and the data (training error) is low. After training the 10 vectors become the class centres. Application of the trained neural network provides a segment volume in which the value at each position is the identification number of the best fitting class centre.

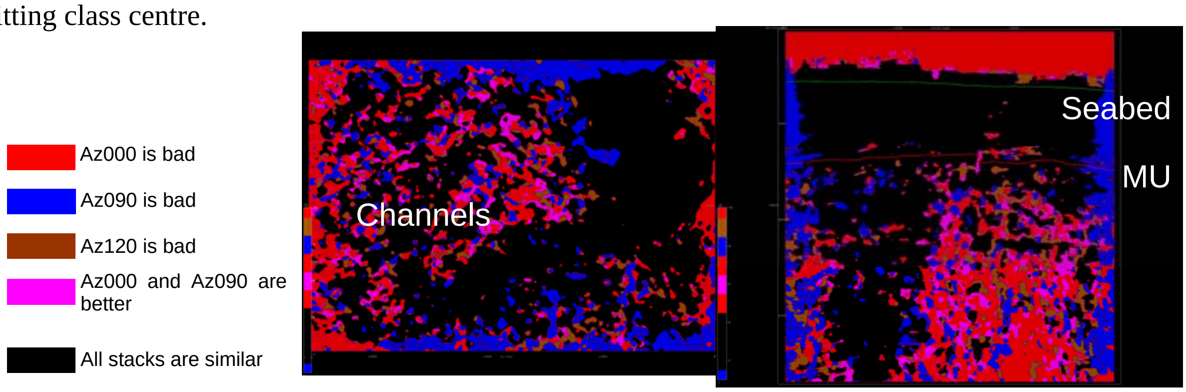

Figure 4 *Segment volume at 3700m (left, depth slice, north oriented) and on a section (right, south-north inline). The legends indicate the signification of the corresponding class centres.*

The visualization of segment volumes (figure 4) on depth slices, inlines and crosslines provides an insight in the spatial variability of the azimuthal stacks. The lack of variation of azimuthal stacks is easily visible in the shallow part. The acquisition-related pattern becomes visible: The east-west azimuthal stack Az090 generates a trend (blue) on the crosslines, which is most visible in the north and south. On the contrary, the north-south stack Az000 generates another trend (red) on the inlines, which is most visible in the east and west. Yet most (other) patterns are not related to the geometry: a large variability can be seen below the shallow channels and the Messinian Unconformity.

The main stacking procedure was created based on the outputs of the unsupervised segmentation, i.e. the class centres and the segment volume, and the prepared stacks. The "UVQ quality based mazstack" can be defined as the weighted sum of the azimuthal stacks using the class centre (quality) attribute as weights, which varies along the segment volume. Furthermore the weights can be trimmed before stacking: For each class centre the weight below a percentage of the maximum weight can be put to zero (rejection level). This allows an automated rejection of the bad stacks and dynamically defines the number of stacks to use for each segment. Quality control is provided by looking at the class centre values to know how many stacks are used for each segment.

The improvements were in general limited but no regression was observed. The rejection level was the decisive criteria with an optimal value at 90%. Using this setting, the number of stack volumes varied between 2 and 5 (maximum). No rejection (0%) gave too few improvements, while values higher than 95% would return only the best stack, with a blocky output. Improved stacking was performed using supervised multi-layered perceptron (MLP) neural networks. The objective was to smooth the transition between the segments by re-training the neural network using both the class centres and a subset of the segment volume as target. The output was one probability volume for each segment. The new MLP mazstack was then created by stacking the UVQ quality-based mazstacks using the probability of each segment as weights, instead of returning only the UVQ sum for the locally best fitting segment. This additional re-stacking maintained the benefits of UVQ stacking while adding smoothness between the segments.

The application of this workflow per offset provided a pre-stack neural network mazstack. The same amount of improvement was observed compared to the post-stack application. However the far offset quality was not good (residual move out, NMO stretch) and reducing the offset range while stacking showed an increase resolution, not obtained after neural network stacking.

Conclusions

This paper shows first the importance of data preparation to optimise stacking across azimuths. From the acquisition until the last processing step, a standardised workflow with fixed parameter settings was applied to all individual azimuthal surveys. This preparation phase resulted in slightly increased amplitudes and better event continuity. An unsupervised quality-based neural network stacking workflow, created in this project, provided some additional uplift. The primary outputs allowed the interpretation of the lateral variation in the stack qualities, while the UVQ-based mazstack managed to increase the overall quality. Finally supervised neural networks were used to smooth the transitions between the segments, providing a more sensible mazstack.

However the improvements can be limited by the quality of the data. Limiting the fold when there is significant residual moveout on the prestack gathers can lead to a better post stack image than applying neural network based stacking. Nevertheless for the same fold, neural networks were always better than a conventional mazstack with incremental gains after each step.

Acknowledgments

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