INTRODUCING DEEP NEURAL NETWORKS FOR ULTRA-FAST TRACK PROCESSING: A NEW EARLY-OUT PRODUCT FOR QC AND INTERPRETATION

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Summary

To improve the imaging of the Barents Sea's Nordkapp basin, either in terms of resolution or geological structure, a new seismic acquisition design was proposed, using a widespread hexa-source sitting on top of 18 non-flat streamers. Imaging this new recorded data required specific and complex processing steps using advanced algorithms to maintain high spatial resolution. This were not easy to handle onboard or through a fast-processing flow, so we implemented an Ultra-Fast Track processing by leveraging the capability of Deep Neural Networks to perform the pre-processing stages, ensuring quality in a limited timeframe. Pseudo-synthetic training sets were built from the first batch of received data and data augmentation was applied, with different setting for each processing steps. This result showed an improved resolution with respect to the legacy volume and was used to start interpreting potential hydrocarbon prospects and initiate the velocity model building. The Ultra-Fast Track also served as a helpful tool to assess the remaining challenges to be faced during the full processing.

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Introduction

The Nordkapp Basin, located in the south-western part of the Barents Sea, is a large, under-explored salt basin with a proven petroleum system containing mature Triassic source rocks. It is characterized by a Mesozoic salt mobilization forming salt diapirs appearing as walls and high seismic velocities in the sediments due to the tertiary uplift. This geological setting self-explains why imaging the Nordkapp Basin is known to be challenging. Despite several exploration campaigns carried out over the past decades, no successful drilling has been achieved in this area. To improve the image of this basin, in terms of either resolution or geological structure, a new seismic acquisition design was proposed (Dhelie et al., 2021), using a widespread hexa-source sitting on top of 18 non-flat streamers. These Top-Sources allow for fully recording the near offsets and providing a high crossline coverage. An additional source, called Front-Source, was also set in front of the streamers to record the long offsets and was mainly designed to help with velocity model building (Salaun et al., 2020).

The data, recorded over an area of 3700km^2, not only has a high trace density count, but also requires additional processing sequences to address the various challenges related to its specific acquisition configuration, such as heavily blended energy, propeller noise and strong direct arrivals coming from the source on top of the spread. These noises require specific and complex processing steps, which are not easy to handle onboard or with a short turnaround. On the other hand, a good quality product was needed to evaluate the benefits of the complex acquisition design and to provide a detailed geological view of the Nordkapp Basin at the very early stage of the project cycle. Therefore, it became obvious that we needed to develop an efficient way to produce such an Ultra-Fast-Track (UFT) product with all recorded data and with good enough quality to achieve its purpose. This paper describes a newly implemented UFT processing solution by leveraging the capability of Deep Neural Networks (DNNs).

Deep Neural Networks for an enhanced processing solution

Jin et al. (2018) describe how DNNs can learn and replicate the result of a classical seismic processing workflow. Indeed, DNNs are known for their ability to extrapolate physical noise models and adapt them to diverse noise content (Mohan et al., 2019). In the case of seismic denoising using DNNs, the main challenge is to provide a training set representative of the full diversity of the data and the ideal output where the targeted noise has been fully removed (i.e., without any primary or noise leakage). In order to fulfil these two requirements, we generated dedicated training sets for each individual processing step followed by a specific data augmentation.

<u>Propeller noise attenuation</u>: The first noise tackled in the sequence was the propeller noise. This noise comes from the boat sailing over the streamers, several hundred meters ahead of the towed sources, and appears as a continuous trend of hyperbolas. To train our network, the propeller noise was extracted in the 3D tau-q domain, by knowing the location of the hyperbola apex and the propagation velocity of the noise in the water layer. To avoid introducing a bias in the network, the extracted noise was added to the half of the receiver spread located far behind the source and thus free of any propeller noise (Figure 1a). With this method, an ideal training dataset was obtained. This was run for several thousand shot points (2D gun-cable couple) randomly selected from the first received drop of data (one out of four). The next challenge was to ensure the diversity of the training set, without having any knowledge of the remaining data to be acquired. The data variability depends upon changes in numerous factors, such as the acquisition devices, the water-layer condition or the geology of the subsurface. In the case of propeller noise, amplitude variation of the noise was used to augment our dataset and to mimic the possible current variations leading the source boat to adapt its engine to maintain a regular speed. The DNN architecture used for this process is designed to jointly build and subtract a noise model from the input data (Peng et al., 2021). The Unet part of the network (red area in Figure 1b) is a weighting layer that acts in combination with a convolutional layer and contributes to generating the noise model. For example, in the case of propeller noise, only the traces below the source vessel will be affected. Following a similar methodology, different training sets were built for each of the next processing steps (Figure 2).

<u>Direct Arrival (DA) attenuation</u>: In conventional towed-streamer acquisition, the DA is weak and does not interfere with the recorded reflections. It can be easily removed by applying a mute. In this

acquisition, as the recorders are right below the source, the DA and its associated bubble affect the signal and are particularly difficult to separate from the reflection energy. Simple muting will leave residual DA bubble and create issues during source designature. For its suppression, a 3D DA model was built using the Near Field Hydrophone (NFH) record. The model was then refined through an inversion performed to calibrate the NFH, to adjust the geometry uncertainties of the source-receiver setting and to ensure a straight subtraction of the DA energy (Salaun et al., 2019). To build the training set, this DA model was added to data from external cables, on which no strong DA energy was observed as they are slightly away from the source position. A data augmentation was done on the training set by changing the amplitude and slope of the DA model before addition to the clean shot points.

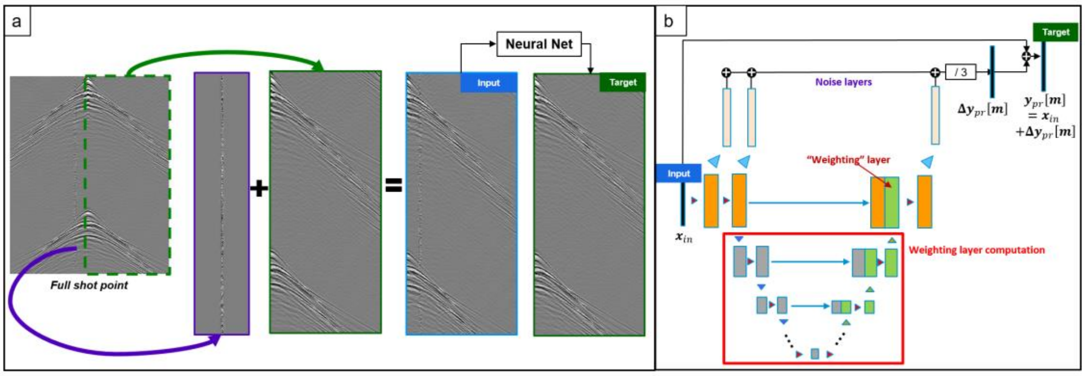

Figure 1: *Training and network architecture. (a) Methodology to build a training set with the example of propeller noise attenuation: From the raw shot point, noise is extracted (purple) and added to a clean part of the data (green). The result of this addition (blue) is our input for the DNN, which will learn to obtain the clean data back (green). (b) DUnet architecture used similar structure of building a noise model prior to subtracting it from input data.*

Deblending: For the UFT product, as we only focused down to 2.5sec record length, we only observed the blended energy coming from the Front-Source. To obtain a Front-Source blended noise model, a 3D curvelet deblending was performed on several sequences, followed by a random selection of several thousand 2D shot points for the training. As the Front-Source shooting rate is sparse, shooting every 11 Top-Sources, we had access to some clean Top-Source shot gathers without any interference noise from the Front-Source. The re-blending was done with the addition of timing and amplitude variability. The use of a linear moveout also helped to generate an augmented training set, anticipating possible velocity variation of the diving waves along the survey. While conventional marine deblending is often performed in 2D or 3D, using the channel domain to take advantage of randomness from the dithering, our DNN method was done in the shot domain. Thus, it eased the data management and avoided any gathering and sorting of the dense data.
3D deghosting: A 3D ghost model was extracted from the data using a tilted hyperbolic transformation (Poole et al., 2018). Numerous re-combinations were then performed as data augmentation, by changing the velocity of the water layer, the reflectivity of the air-water interface or the depth of the cable.
On all the above-described processing steps (with results shown in Figure 2), DNN was trained on several thousand 2D shot points. Thanks to the repetitive nature of the tackled noise, and the data augmentation approach, our training set was sufficient to generalize the DNN application over the entire survey of one million 3D shot points.
Once these DNN-based processing steps were done, we used conventional physical-based algorithms to tackle the rest of the processing steps (such as demultiple and migration), as they are more sensitive to the geology or better explained by physical equations.

Ultra-Fast Track result and discussion
The entire pre-stack depth migrated UFT volume was produced and delivered only 7 days after the last received data drop. This very early product helped to provide a detailed overview, confirm the quality of the acquired data and replace the usual on-board sub-optimal Fast-Track volume. It also served as a benchmark for the full processing and imaging work, providing an early seismic volume in this area where no existing image was available. The interpreted structural horizons (Figure 3a) were useful for

both understanding the regional geology, especially around the complex salt bodies, and supporting the velocity model building work. It also helped to identify some hydrocarbon prospects (Figure 3b) and some key areas of interest for the remainder of the processing project (e.g., noisy lines, complex geological areas). In addition to the structural image, CDP gathers were used to perform a preliminary AVO analysis and provided key information for the velocity model building. This first available RMO information allowed an early tomography to improve the initial velocity field coming from merged vintage 2D models.

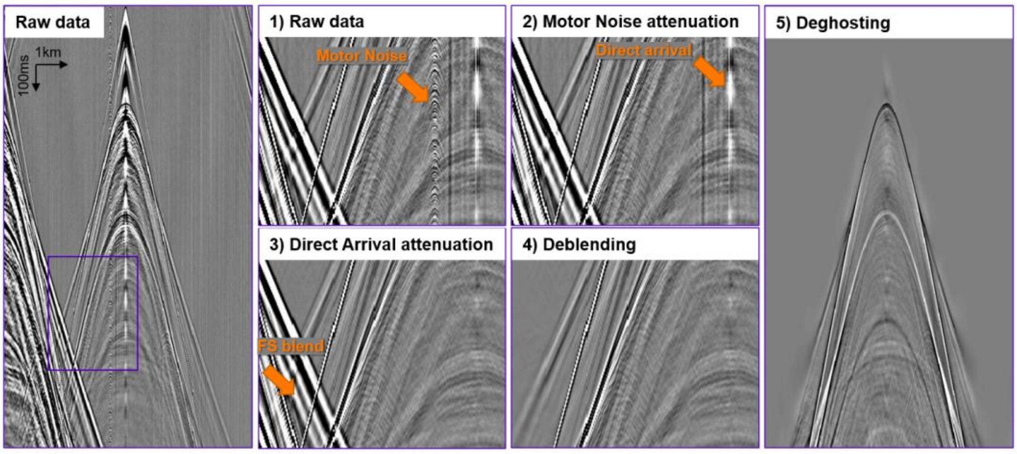

Figure 2: *Example of a shot processed using DNN from raw data to the demultiple input with the corresponding tackled noise highlighted for each step.*

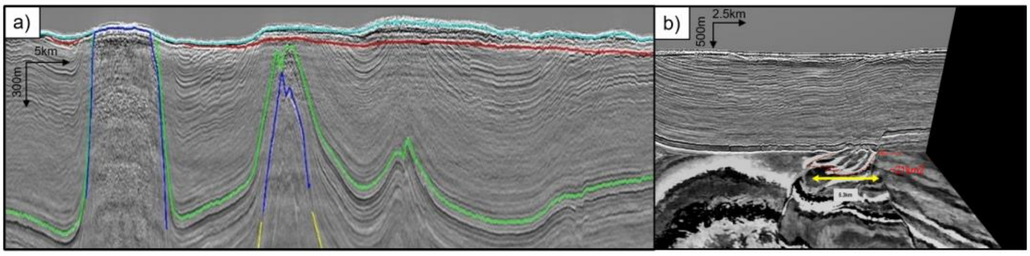

Figure 3: *Ultra-Fast Track data provided valuable information for project assessment: (a) First structural interpretation leading to first large-scale salt picking; (b) Early analysis of potential hydrocarbon prospect over a sedimental trap.*

We compared our Nordkapp UFT volume with a small 3D vintage volume at the overlapping area. Thanks to the density of the new acquisition design and its native bin size of 6.25m x 6.25m, the UFT volume exhibits higher spatial resolution compared to the legacy volume (Figures 4a, 4b). The fault networks show better definition, and the sharpness of the events is improved on both the cross-section and time-slice. Salt flank focusing and imaging are also improved and aided understanding of how the salt bodies are interconnected with the sediment layers, just a few days after the end of acquisition. Out of our curiosity, we compared this 7-day 4ms sampled UFT product to an around-6-month, full-blown, 2ms sampled conventional production result (Figure 4c). It showed that even if good quality was reached during the short UFT timeframe, DNN-based processing using current training sets (less than 0.01% of the full data) has not yet reached the quality offered by high-end algorithms and detailed workflows. However, it is able to provide a fit-for-purpose volume that goes beyond onboard fast track processing with short turnaround.

Conclusion

The advanced and high-density acquisition set-up, designed to overcome seismic imaging challenges of the complex Nordkapp Basin geology, generated unique challenges to produce an onboard Fast-Track product that utilizes all the input data. Without resorting to the data decimation trick, or to cheaper-faster-worse algorithms, we leveraged the capability of Deep Neural Networks for the key pre-processing stages of the UFT, replicating advanced 3D processing steps in 2D and hence ensuring decent quality within a limited timeframe. Pseudo-synthetic training sets were built from the first batch of received data and data augmentation was applied, with different settings for each processing step. In the future, further refinement in the neural network architecture and the training set generation may help to improve the DNN processing quality to be more complementary to the physics-based algorithms. The comparison made with the full-blown high-resolution production result indeed showed that the DNN-based method cannot yet outperform conventional processing algorithms but can be a useful tool to improve them. However, the UFT result, obtained only 7 days after receiving the last data drop, showed significant value with respect to the legacy final volume and was used to start interpreting potential hydrocarbon prospects. This product was also valuable to start the velocity model building and to reveal the multiple processing challenges that remain to be addressed during the full processing.

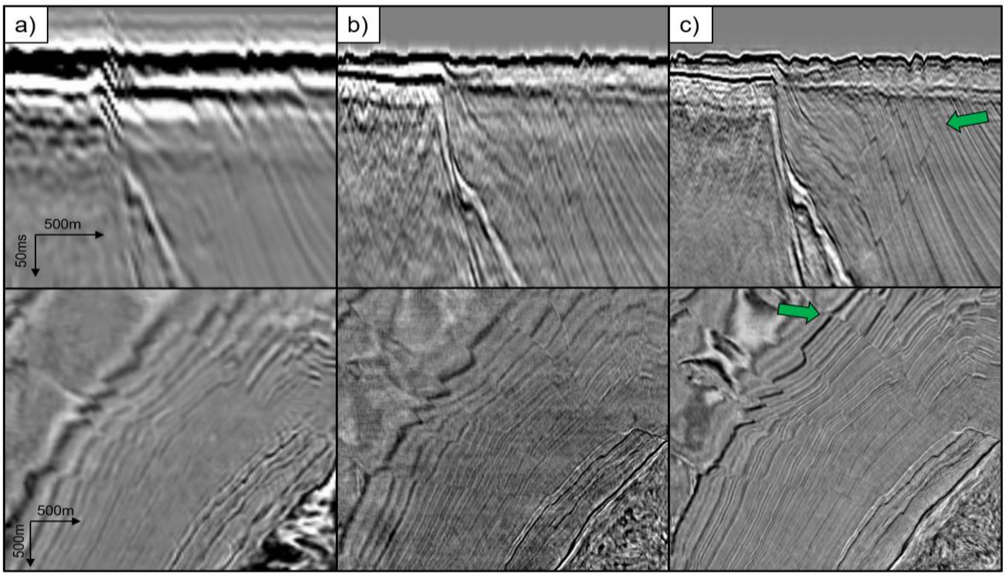

Figure 4: *Inline cross-section (top) and time-slice (bottom) comparison between 3D vintage data (a), Ultra-Fast Track volume (b) and Full-blown high-resolution (c). Sharp fault network, created by salt tectonics, is gradually improved (green arrows).*

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