Computing seismic attributes with deep-learning models

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***Abstract*—Seismic data contains valuable information about the Earth's subsurface, which is useful in oil and gas (O&G) exploration. Seismic attributes are derived from seismic data to highlight relevant data structures and properties, improving geological or geophysical data interpretation. However, when calculated on large datasets, quite common in the O&G industry, these attributes may be computationally expensive regarding computing power and memory capacity. Deep learning techniques can reduce these costs by avoiding direct attribute calculation. Some of these techniques may, however, be too complex, require large volumes of training data, and demand large computational capacity. This work shows that a conventional U-Net Convolutional Neural Network (CNN) model, with 31 million parameters, can be used to compute diverse seismic attributes directly from seismic data. The F3 dataset and attributes calculated on it were employed to train the models, each specialized in a specific attribute. The trained CNN models yield low prediction errors for most of the tested attributes. These results evince that simple CNN models are able to infer seismic attributes with high accuracy.**

I. Introduction

Seismic processing is a critical component of oil and gas exploration due to its ability to provide valuable insights into the subsurface geology, enabling companies to make informed decisions about where to drill and extract these valuable resources and reduce exploration risks. Seismic processing involves analyzing the echoes of seismic waves that travel through the Earth's subsurface after being artificially generated by controlled explosions or vibrations. These echoes, or reflections, contain information about the various layers of rock, fluid, and other geological structures present beneath the surface.

Seismic attributes are specific characteristics derived from seismic data through complex mathematical analysis. These attributes offer additional information beyond the traditional seismic images and aid geophysicists and geologists on several exploration tasks, including identifying seismic facies (horizontal and homogeneous structures of the same rock material) [7], [13], horizon detection [12], and fault detection [11]. Moreover, seismic attributes are used to characterize previously discovered reservoirs to maximize oil and gas production.

Seismic attributes are generated via mathematical computations, which can be quite time-expensive depending on the specific attribute in question. For example, when a substantial surrounding area impacts each point within a three-dimensional attribute, the outcome is a computation that demands significant processing resources. Furthermore, this analytical procedure can impose a substantial computational burden when dealing with huge seismic datasets.

Prior research has demonstrated that deep neural networks can be effectively trained for the efficient computation of these attributes [8]. This strategy streamlines the calculation procedure by condensing it into a set of matrix multiplications, which can be readily parallelized using established computing tools like GPUs. Navarro *et al.* [8] demonstrated that seismic attributes can be efficiently calculated $80\times$ faster using Generative Adversarial Networks (GANs).

In this work, we show that various seismic attributes can also be accurately estimated (predicted) using U-Net, a simpler architecture compared to GANs. Moreover, training a U-Net requires less data and computing power than GANs. Alternative strategies for addressing the posed issue may involve other simple convolutional neural network (CNN) models, such as LeNet [3] and Fully Connected Network (FCN) [2], [10]. However, this study is directed toward the traditional U-Net model. Our results demonstrate that predictions are highly accurate for almost all attributes based on complex seismic traces.

The remainder of this paper is organized as follows: Section II explains the experimental methodology. Section III presents and discusses the results obtained. Finally, Section III concludes the paper.

II. Methodology

The pipeline followed in this work is illustrated in Figure 1. The seismic dataset was obtained and pre-processed. After this, different attributes were calculated for the seismic dataset

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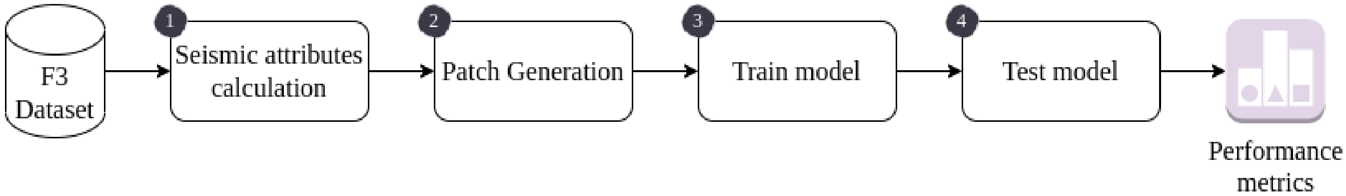

Fig. 1: Train and evaluation pipeline.

(step 1). Once the data were generated and annotated, 2D arrays were obtained to train and test the model (step 2). Afterward, a specific CNN model was trained for each attribute (step 3). Finally, the trained model is tested with the test set, generating the performance metrics (step 4).

A. *Dataset specifications*

The F3 Netherlands open dataset provided in [1] was employed in SEG-Y and subsequently converted to NumPy and Zarr format. This dataset is already normalized through the standard norm. Various attributes were calculated on this dataset to annotate it, namely, Envelope, Amplitude Acceleration, Apparent Polarity, Cosine Instantaneous Phase, Instantaneous Phase, Relative Amplitude Change, Sweetness, LBP 3D, and Semblance. The dataset split methodology follows the one in [1].

Our dataset consists of two three-dimensional (3D) datasets, which we refer to as cubes. One of these is the seismic data, while the other is the seismic attributes. The 3D seismic data is a volumetric dataset resulting from the combination of seismic traces acquired from diverse directions and depths. Seismic traces are individual data records collected at designated receiver positions, providing information within a single measurement path. In a 3D seismic cube, a slice parallel to one of the dimensions forms a set of seismic traces known as inlines, while slices parallel to another dimension are referred to as crosslines. The dimensions of the training cube are $(400, 701, 255)$, whereas those of the testing cube are $(200, 701, 255)$. The first dimension corresponds to inlines, the second to crosslines, and the third to time.

B. *Pre-processing*

These three-dimensional arrays were then sliced into several two-dimensional matrices, the inlines. Thus, the data used for training and testing the network are matrices of $(701, 255)$.

An atypical large error was found in all analytical attributes employing the Hilbert transform. The calculation of this transform depends on previous values, generating an attribute value with a different pattern for the first value of each seismic trace. This makes it difficult for the model to learn such a random pattern. Thus, the result metrics were calculated by excluding those values in the test. The drawback to this removal is the absence of those points in the final inferred attribute, but the performance metrics are drastically improved.

C. *Neural Network Architecture*

The CNN model used in this work was adapted from [6] and [9]. As illustrated in Figure 2, the network has five levels of convolutions for both input and output. Four 2x2 max pooling layers followed by two 2D convolutions with kernel size 3 and padding 1. The up-convolutions use the 2D tensor generated in the down-convolutions and are followed by two kernel size 2 2D convolutions. The convolutions and padding are the standard functions of the PyTorch neural networks library. Finally, there is an output convolution with a kernel size of 1. Each level has a different number of feature maps.

D. *Infrastructure Setup*

In all experiments, we used a batch size of 64 and the mean squared error (MSE) loss function. The maximum number of epochs was set to 200 in the training stage, and the validation set is 10% of the training set. The experiments were executed in the OGBON Supercomputer, using one computational node with four NVIDIA Tesla V100 SXM2 GPUs. The learning rate follows the learning rate scheduler "CyclicLR" varying from 10^{-3} to 10^{-5}. The following metrics were used to evaluate the model: MSE, RMSE, MAE, PSNR, SSIM, and R^2.

III. Results and Discussion

Table I demonstrates the performance metrics obtained with the trained model for each seismic attribute considered in this study. A specific model was trained to predict a particular attribute. In general, the trained models performed well for almost all the attributes assessed, except for the Instantaneous Phase and LBP 3D attributes considering PSNR and SSIM metrics, while Sweetness and LBP 3D underperformed in the R^2 metric. This indicates that the U-Net model was able to approximate quite well the function implemented by most of the attributes considered.

Figure 3 presents an example of a U-Net predicted attribute (Pred) for each attribute considered in this study, its corresponding analytical calculation (Gr. T), and the differences between those two (Diff). All predictions were made on the inline 4 of the test dataset. Most of the considered attributes presented a very similar visual shape and yielded low errors between the analytical and the predicted attributes.

To better illustrate the error performance, Figure 4 shows the trace 23 of the inline 4 for the selected predicted attributes. All the predicted traces for attributes with good performance metrics values follow very close its corresponding analytical trace. For instance, Envelope (Figure 4a), which yielded good

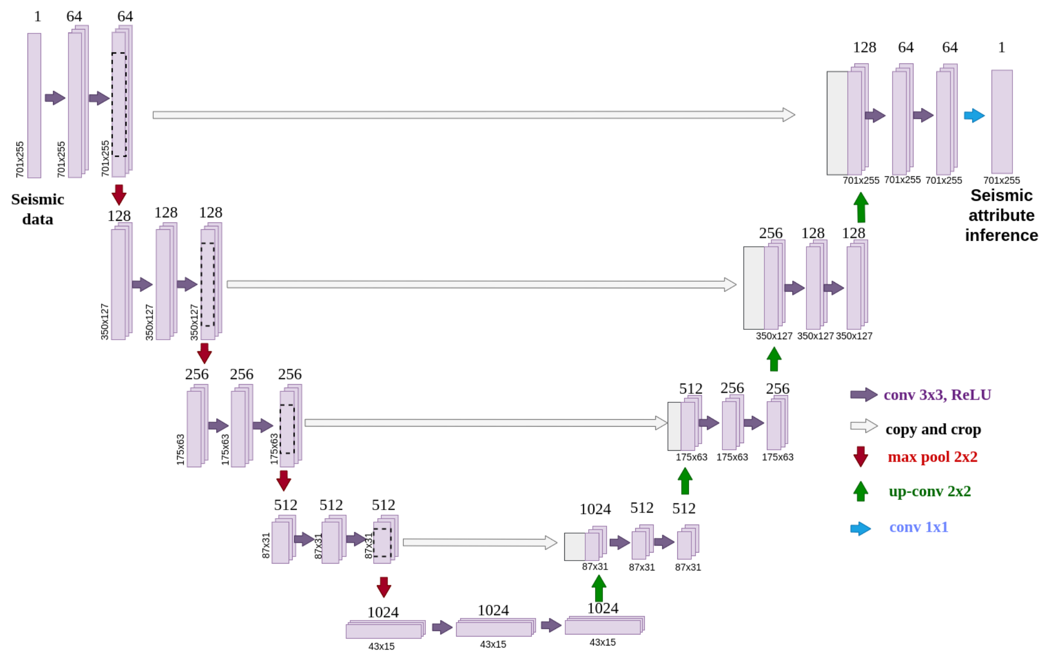

Fig. 2: The U-Net architecture employed in this work.

results in all performance metric, followed well the signal shape with just a few prediction errors. Interestingly, Semblance (Figure 4i), which scored low in the R^2 metric, also follows well the shape of the analytical attribute; As expected, Instantaneous phase (Figure 4d) and LBP 3D (Figure 4h), which are the attributes underperforming in the R^2 score and PSNR metrics, are the ones more discrepant in the figure, evincing a bad performance following the analytical trace.

A. Limitations

It was evinced that the trained models have a great learning capacity for predicting a seismic attribute. However, prediction errors occur for some attributes, particularly, for instantaneous phase and LBP 3D. The latter is a 3D attribute and may require neighborhood information to improve the model prediction performance. This information, however, is not fully captured with the 2D model employed in this study.

TABLE I: Performance metrics for different seismic attributes.

Attribute	MSE	RMSE	MAE	PSNR	SSIM	R2
Envelope	0.0003	0.0183	0.0131	39.3533	0.9804	0.9833
Apparent Polarity	0.0189	0.1303	0.0670	21.6219	0.8107	0.8722
Cosine Instantaneous Phase	0.0044	0.0615	0.0361	23.4770	0.9834	0.9901
Instantaneous Phase	2358.8037	47.4073	34.2836	11.3785	0.6686	0.7690
Relative Amplitude Change	0.0041	0.0597	0.0367	23.8015	0.9172	0.9711
Amplitude Acceleration	0.0023	0.0466	0.0323	26.2879	0.9473	0.9688
Sweetness	0.00005	0.0069	0.0047	28.9432	0.8434	-46.6401
LBP 3D	99.0772	9.9386	8.1093	11.1663	0.2462	-0.0110
Semblance	0.0048	0.0667	0.0438	23.1695	0.8008	0.6620

It is still not clear whether these errors are relevant to geologists, geophysicists, or even to other neural network models performing a task that employs an attribute as input, for instance, semantic segmentation of seismic facies [5]. Thus, the impact of the observed errors on tasks in which the attributes are employed deserves further analysis. If the performance of this CNN model is not enough for a given application, thus, more complex techniques to attribute calculation may be still necessary, such as 3D CNN models, GANs [8] or transformers [4].

IV. Conclusion

This work has demonstrated the feasibility of using the U-Net convolutional neural network to calculate seismic attributes, whose outputs are very similar to those calculated mathematically. The network scores differently for each seismic attribute, producing generally better results for continuous attributes, such as envelope, and slightly worse results for instantaneous phase and LBP 3D. In many cases, the difference between the inference and the ground truth cannot be visually identified without some help, such as the calculation of the differences between the images. It is necessary to understand whether this error is relevant for tasks employing the attributes, such as neural networks to predict seismic facies or horizons.

The constant inference speed of the CNN regardless of the trained attribute being calculated is a strong motivation to train deep learning models to replace the calculation of seismic attributes, especially those more expensive computationally.

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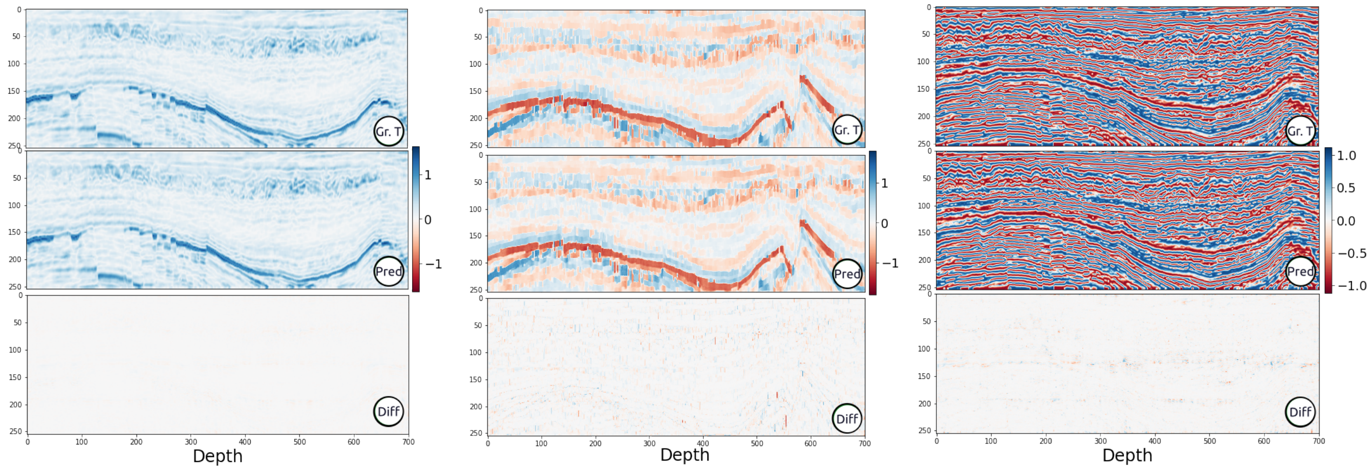
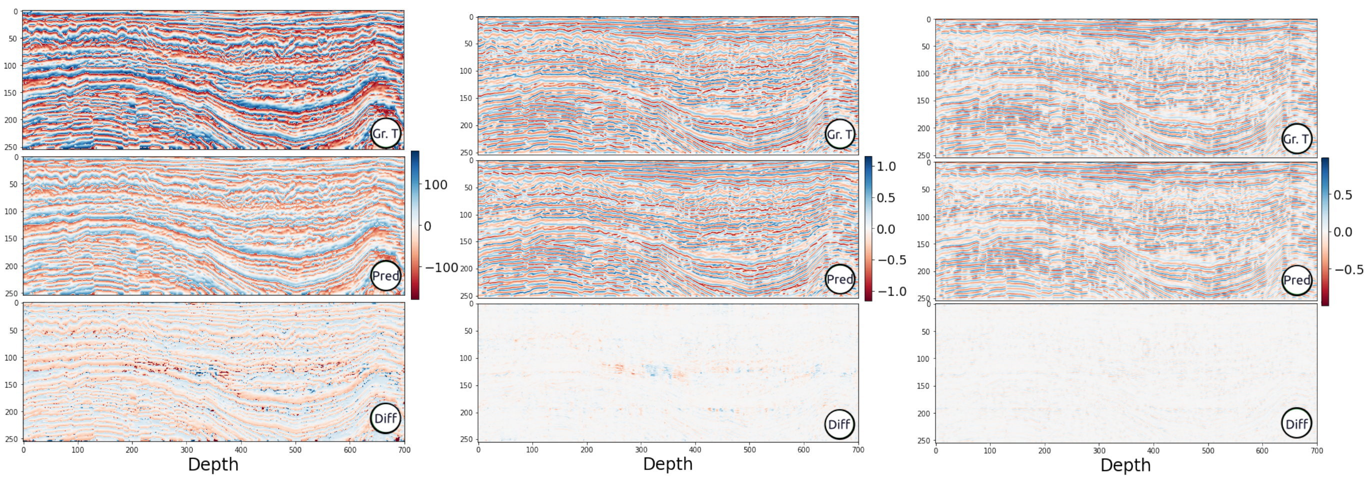
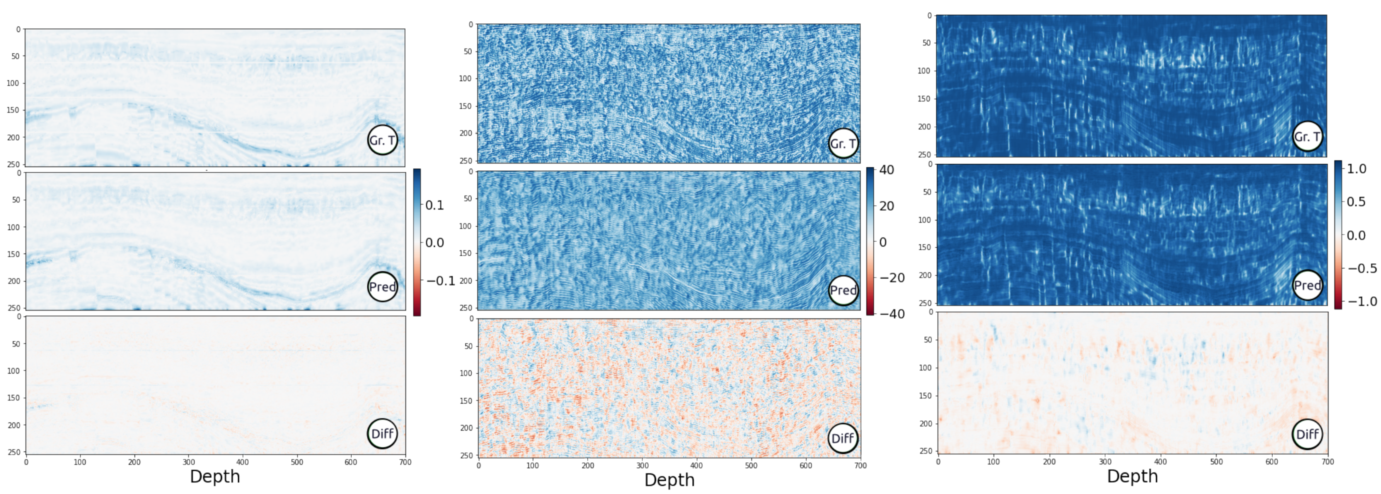


(a) Envelope (b) Apparent Polarity (c) Cosine Instantaneous Phase



(d) Instantaneous Phase (e) Relative Amplitude Change (f) Amplitude Acceleration



(g) Sweetness (h) LBP 3D (i) Semblance

Fig. 3: Prediction and error performance of the trained model for each attribute assessed. From up to down in each image: (Gr.T) ground truth data, (Pred) prediction, and (Diff) their difference. The scale for the three images is the same and is shown on the right side. All the attributes were inferred or calculated on inline 4 from the F3 dataset.

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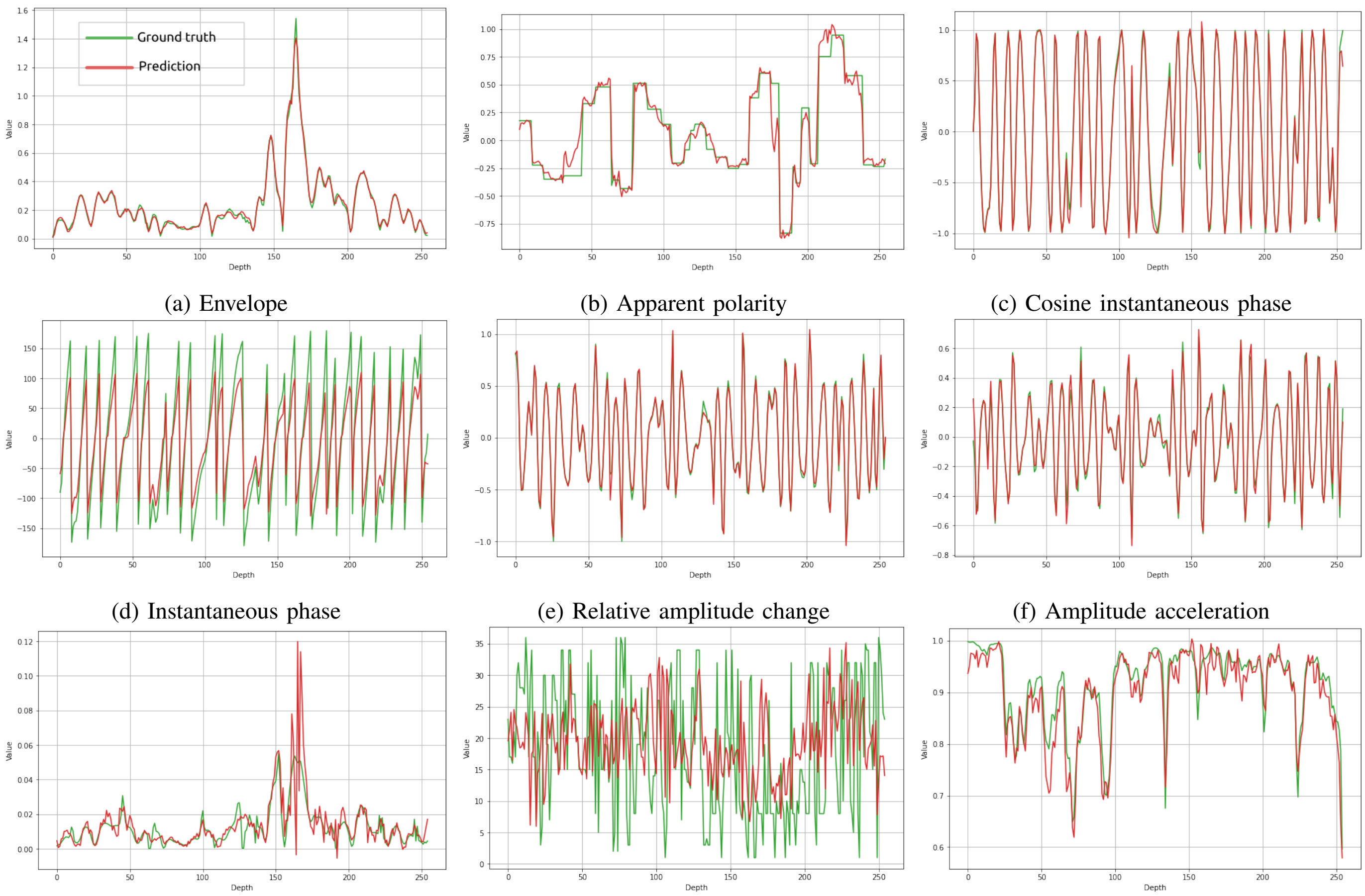

(a) Envelope (b) Apparent polarity (c) Cosine instantaneous phase

(d) Instantaneous phase (e) Relative amplitude change (f) Amplitude acceleration

(g) Sweetness (h) LBP 3D (i) Semblance

Fig. 4: Seismic trace 23 of inline 4 for the attribute considered in the study. The green one is the trace obtained from analytical calculation and the red one is the inference produced by the model.

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