Automatic gas detection using seismic data and Transformer neural networks

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Abstract

Anomalous seismic attributes known as Direct Hydrocarbon Indicators (DHI) are used to identify hydrocarbons in oil and/or gas reservoirs. However, in most situations, these anomalies are hardly detected due to the large amount of data to be interpreted. Nowadays, deep learning techniques are used to solve problems that consume time and demand human effort with good accuracy. In this study, a methodology to detect gas using seismic data and a Transformer Neural Network is presented. That methodology has been applied considering offshore and onshore seismic data. The presented results show a good accuracy and demonstrate the capabilities of this proposal for exploration purposes.

Introduction

Seismic reflection is one of the most used geophysical methods in the oil and gas (O&G) industry to extract data related with the structure of subsurface layers, lithology and rock properties (Pochet et al., 2018; Di et al., 2018; Chevitarese et al., 2018). Furthermore, through seismic reflection, the location and volume estimates of gas accumulations can be inferred for reducing the geological risk of exploration wells (Santos, 2019; Morton-Thompson et al., 1993). However, as large amount of information is produced, considerable effort and time from specialized teams is required to interpret the seismic data.

In the literature, the use of machine learning techniques together with the extraction of seismic attributes have been used to help geoscientists in seismic interpretation (Guitton et al., 2017; Di et al., 2017). For instance, Araya-Polo et al. (2017) used deep neural networks trained with synthetic data to detect seismic faults. Chevitarese et al. (2018) used Convolutional Neural Networks (CNN) and Zhao (2018) used an image segmentation network for the classification of seismic facies.

Santos (2019) and Santos et al. (2019) proposed a novel methodology to detect DHIs on seismic data applying a Long Short-Term Memory (LSTM) neural network on the seismic trace scale. In their proposal, each seismic trace is divided into patches that are the entrance to the LSTM network along with the labeling of each patch. Then, the network generates a probabilities map to detect gas in each region of the seismic image. For train, test and validation, Santos (2019) used the public offshore data from the Netherlands F3-Block. More recently, Santos et al. (2020) improved such methodology taking into account Transfer Learning and presented applications in onshore data in some areas of the Parnaíba basin known as ”Parque dos Gaviões” de Miranda et al. (2018). The tests showed satisfactory predictions of gas detection considering onshore and offshore surveys. Moreover, that methodology can be adopted with 2D or 3D seismic acquisitions. However, for exploratory fields, without any indication of gas, there are still some uncertainties regarding the effectiveness of such methodology.

In order to reduce such uncertainties, in this study is proposed a new artificial intelligence technique based on a Transformer Neural Network for applications of natural gas detection. The Transformer is a deep learning model introduced recently in 2017 by Vaswani et al. (2017) that uses the mechanism of attention. The main applications have been in the area of natural language processing (NLP). Owing to its capabilities for parallelization during training, Transformer has replaced previous neural network models on NLP problems (Wu et al., 2020). In this sense, the proposed methodology in this study (Figure 1) is similar to that initially presented by Santos (2019), but uses a Transformer Neural Network designed for gas detection. For comparison purposes between LSTM and Transformer, data corresponding to the Netherlands F3-Block and Parque dos Gaviões are considered. The results are compared in terms of accuracy, sensitivity, specificity and area under roc curve (AUC).

Materials and Methods

In this section, the proposed methodology to detect gas is described in three steps as illustrated in Figure 1. In the first step, the seismic data used in this study are briefly introduced. In the second step, some preprocessing techniques required for data preparation are discussed. Finally, in the third step, the Transformer neural network used to perform the experiments is described.

Seismic Data

The experiments performed in this study are based on three seismic datasets. The first considers the Netherlands Offshore F3-Block, a public repository that can be accessed at the Open Seismic Repository dGB Earth Sciences (1987). This dataset contains 384 square kilometers of time migrated 3D-seismic data that includes 651 inline interval and 951 crossline interval and a time range of 1848 ms, with a sampling of 4 ms (Kushwaha et al., 2020).

The second and third seismic datasets correspond to the paleozoic Parnaíba Basin located in the northeast region of Brazil. Parnaíba is a classic oval-shaped intracratonic basin, covering an area of more than 600,000 square kilometers and a maximum thickness of 3,500 m. The geological mapping of this region started in the twentieth century (1909-10) aiming to find coal and fresh water

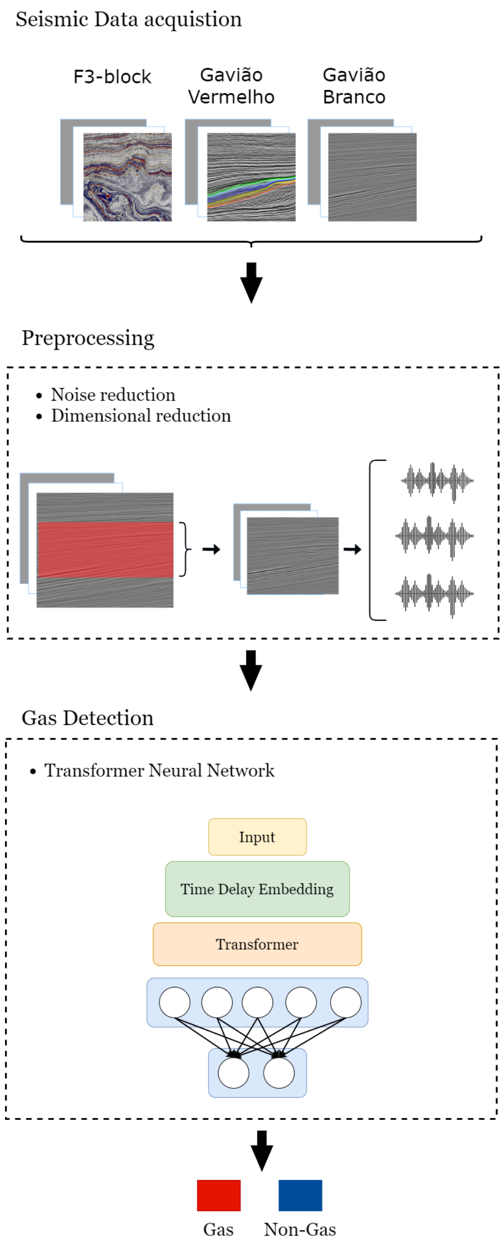

Figure 1: Flowchart of the method

reserves. Subsequent explorations have focused on the detection of oil and gas, producing new 2D and 3D geological maps (de Miranda et al., 2018). The available data consist of three hundred and eighty 2D seismic lines, corresponding to the area known as ”Parque dos Gaviões”, later divided into named fields: Gavião Real, Gavião Azul, Gavião Branco, Gavião Branco Norte, Gavião Vermelho, Gavião Caboclo and Gavião Preto (Figure 2). Among them, Gavião Vermelho and Gavião Branco were chosen in this study due to their greater availability of seismic data. Those data were provided by Eneva, a Brazilian company of power generation.

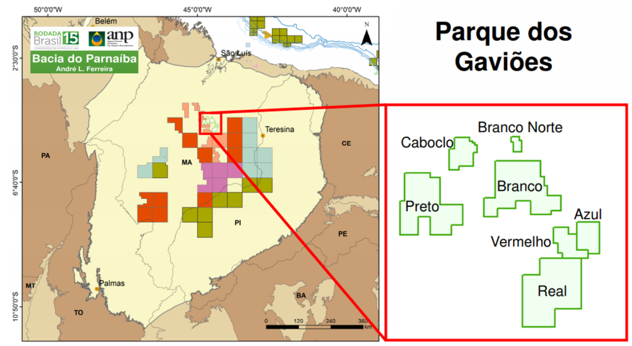

Figure 2: Parque dos Gaviões (de Miranda et al., 2018)

Preprocessing

Similar to Brownlee (2018) and Santos (2019), the proposed methodology uses a one-dimensional signal approach. However, the first dataset is composed of 3D seismic data while the second and the third datasets are composed of 2D seismic data. Moreover, onshore seismic data are in general quite noisy. Therefore, preprocessing steps are performed in order to perform the one-dimensional signal approach and to mitigate the noise effect of the seismic data. Those steps consist on noise and dimensionality reduction. Firstly, the number of samples for the analyses are reduced by delimiting, in time and length, a ROI that may contain gas. Such process is performed in each dataset to indicate the gas patterns that the Transformer neural network model must learn to identify. Based on field data, drilled exploration wells and interpretation, Eneva's geoscientists delimitated the ROI in the datasets of Gavião Vermelho and Gavião Branco. Then, seismic traces are extracted from each seismic data and finally, a windowing process is applied to extract samples of size 65x1 with superposition and step size of 1. It is worth mentioning that each sample must have a minimum size sufficiently capable of carrying useful information from neighboring regions (Santos et al., 2019).

Gas Detection using Transformer Neural Network

Following the proposed methodology, the next step is to classify the seismic trace samples in ”gas” or ”non-gas” through the Transformer neural network. Transformer does not use recurrence and convolution, but self-attention mechanisms to draw global dependencies between input and output data. Due to that feature, Transformer can perform significantly more computation in parallel (Vaswani et al., 2017). Moreover, Transformer is an encoder-decoder architecture. The encoder consists of six identical encoder layers stack. Each encoder layer has the same architecture and is composed of two main components: self-attention and a feed-forward neural network. The decoder is quite similar to the encoder, both have the same layers, but between them there is an extra attention layer. Figure 3 shows the Transformer architecture adopted in this study. It consists of a Time Delay Embedding layer (Pan and Duraisamy, 2020), a Transformer, and two fully connected layers. Then, dropout techniques between fully connected layers are applied. A dropout rate of 0.1 is used for each sub-layer. Figure 4 shows the proposed model. As a result, a binary classification of gas and non-gas is obtained. Finally, some validation metrics such as accuracy (Acc), sensitivity (Sens), specificity (Spec), and area under roc curve (AUC) are used to check the efficiency of the proposed method (Duda, 1973).

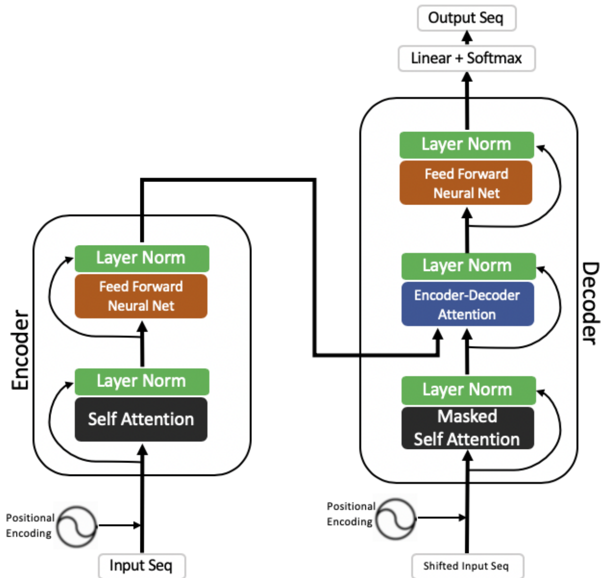

Figure 3: Transformer Neural Network adapted from Dugar (2019)

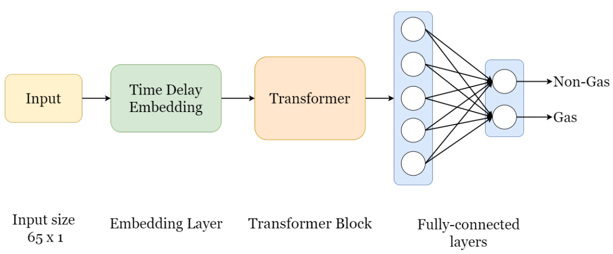

Figure 4: The Transformer-based proposed model

Results and Discussion

For evaluation, each dataset was divided into three subsets: 60% for training, 20% for validation and 20% for testing. Table 1 shows the number of samples with gas and non-gas in each dataset.

Table 1: Gas and non-gas samples by dataset.

Field	Set	Gas	Non-Gas
F3-block	Train	1,154,386	5,159,114
	Validation	237,408	9,775,092
Gavião Vermelho	Train	9,570	656,050
	Validation	4,950	192,884
Gavião Branco	Train	43,130	3,193,562
	Validation	12,650	1,075,634

It is observed that the three datasets are quite heterogeneous regarding the number of samples. Moreover, all the datasets have more negative samples than positive, becoming difficult for the model to differentiate the two classes. Therefore, the sample proportion at each dataset was balanced to solve this issue. In this sense, samples labeled as non-gas were randomly selected maintaining a proportion of 1 gas-sample to 4 non-gas samples towards realizing experiments with unbalanced data, which is expected for the problem.

Regarding internal Transformer parameters, the embedding size, the number of attention heads and the hidden layers in the feed-forward network are set to 20, 10 and 32, respectively. The Transformer model was trained with 100 epochs using a batch size with 64 samples, the ADAM optimizer function was considered with a fixed learning rate of 1e-5 and a binary cross-entropy as a loss function. Table 2 presents the resultant metrics in all datasets using Transformer. For comparison purposes, Table 3 shows the metrics achieved by Santos (2019) for the F3 block.

Table 2: Classification results using Transformer

Dataset	Metrics			
	Acc (%)	Sens (%)	Spec (%)	AUC (%)
F3 Inline	94.51	95.05	94.50	94.78
F3 Crossline	97.33	94.30	97.30	95.85
Gavião Vermelho	98.93	59.75	99.20	79.48
Gavião Branco	97.03	68.87	97.25	83.06

Table 3: Classification results using LSTM (Santos, 2019)

Dataset	Metrics			
	Acc (%)	Sens (%)	Spec (%)	AUC (%)
F3 Inline	97.16	97.83	97.15	98.80
F3 Crossline	96.83	94.77	96.87	98.81

Considering the Inline seismic sections from F3-dataset, it is observed that Santos (2019) obtained slightly better results in all metrics. However, from the comparison of the Crossline seismic sections, the current proposal show a slight improvement. Figure 5 shows the output prediction using the Transformer neural network in F3-dataset. The red regions in the ground truth represent potential gas regions defined through interpretation of geoscientists and the green regions in the output model represent the corresponding predictions. It is noticed that the model results match very well with the expected gas regions.

From the results in Gavião Vermelho and Gavião Branco, good accuracy and specificity are obtained. However, sensitivity and AUC presented metrics significantly lower. This contrast in the results can be attributed to the quality of the seismic data, since the seismic datasets from the Parnaíba Basin are noisier than those of the F3-block. Consequently, the model can generate miss-classified samples. Moreover, the gas reservoir layers in Parnaíba's Basin are more difficult to classify owing to the quality of the seismic data. Besides, Gavião Vermelho and Gavião Branco have fewer samples than the F3-block and that could explain the lower metrics in sensitivity. Therefore, the

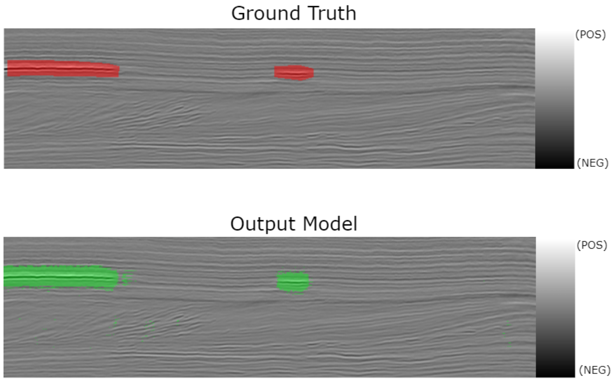

Figure 5: Ground Truth and output model (F3)

predictions in those fields presented blemishes and some false positives, as illustrated in Figure 6 and Figure 7. Even so, the models were capable of predicting potential gas regions.

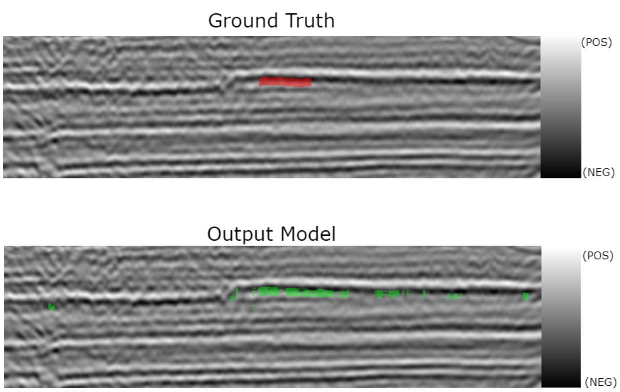

Figure 6: Ground Truth and output model (Gavião Vermelho)

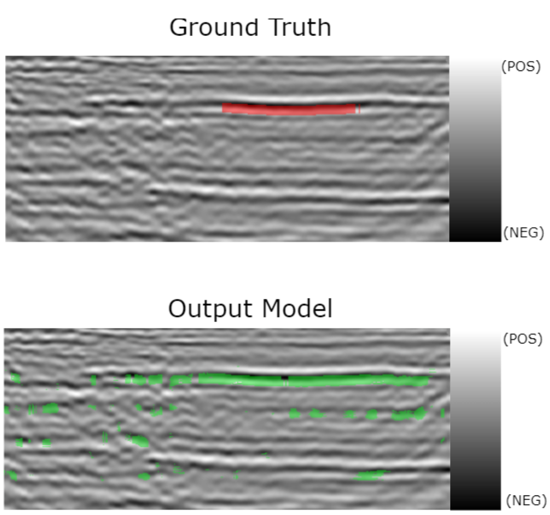

Figure 7: Ground Truth and output model (Gavião Branco)

Conclusions

A methodology based on Transformers neural network to detect gas using seismic data was presented in this study. Compared to deep learning-based sequence networks, the proposed model uses self-attention mechanisms for learning complex dependencies in seismic data samples. Since its recent introduction, Transformer has been used for natural language processing. Therefore, this is the first time that such neural network is applied with seismic data to detect potential gas regions.

The proposed methodology uses a one-dimensional signal approach. Therefore, it can be used with 2D or 3D seismic acquisitions, but some steps are necessary to prepare the data before performing the tests. In total, three datasets are used in this study. The first correspond to offshore seismic data from the F3-Block in Netherlands and the others are onshore data from Parnaíba's Basin in Brazil.

According to the metrics used to check the results quality, the proposed neural network achieved good predictions in comparison with previous solutions reported in the literature. In relation to the F3-block, the model predictions matched very well with potential gas regions, showing excellent metrics in accuracy, sensitivity, specificity and AUC. Regarding Gavião Vermelho and Gavião Branco, the proposed model was also capable to detect expected gas regions. Yet, owing to the limited number and the low quality of seismic data in onshore acquisitions, the model predicted some regions with false positives which can be responsible for the low metrics obtained in sensitivity. Further research is being carried out to improve the handling of onshore seismic data. However, in general, it was demonstrated that the proposed methodology is promising and can assist experts in detecting possible gas signatures on seismic data during exploration phases.

Acknowledgments

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